Commodity Pricing, Credit and Capital Flows: The Role of Financial Intermediaries

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In memory of Hedwig

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Erklärung zu Ko-Autorenschaften

Diese Dissertation besteht aus vier (Arbeits-)Papieren, von denen eines in Zusammenarbeit mit zwei Koautoren und eines mit einem Koautoren entstanden ist. Der Eigenanteil an Konzeption, Durchführung und Berichtsabfassung der Kapitel lässt sich folgendermaßen zusammenfassen:

- ***"Nonlinear Intermediary Pricing in the Oil Futures Market"*** mit Malte Rieth und Anton Velinov

  Eigenanteil: 33 Prozent

- ***"An Empirical Characterization of Commodity Futures Trading"*** mit Malte Rieth

  Eigenanteil: 50 Prozent

- ***"Macroeconomic Effects of Loan Supply Shocks: Distinguishing Between Business and Household Loans"***

  Eigenanteil: 100 Prozent

- ***"Global European Banks and the Global Financial Cycle"***

  Eigenanteil: 100 Prozent

Liste der Vorpublikationen

Working Papers

Eine ältere Version des ersten Kapitels ist als Working Paper erschienen:

Bierbaumer, D., Rieth, M., und Velinov, A. (2017). Nonlinear Intermediary Pricing in the Oil Futures Market. DIW Berlin Discussion Paper Nr. 1722.

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List of Abbreviations

AIC . . . Akaike information criterion
AR(1) . . . Autoregressive (model) of order 1
BIS . . . Bank for International Settlements
BLS . . . Bank Lending Survey
BOPS . . . Balance of Payments Statistics
CFTC . . . Commodity Futures Trading Commission
CIT . . . Commodity index trader
CPO . . . Commodity pool operator
CTA . . . Commodity trading advisor
DCOT . . . Disaggregated Commitments of Traders (report)
DSGE . . . Dynamic stochastic general equilibrium (model)
EBP . . . Excess Bond Premium by Gilchrist and Zakrajšek (2012b)
ECB . . . European Central Bank
EM . . . Expectation maximization (algorithm)
EONIA . . . Euro OverNight Index Average
EUR . . . Euro / eurozone
FAVAR . . . Factor-augmented vector autoregressive (model)
FE . . . Fixed effect
Fed . . . Federal Reserve System
FGLS . . . Feasible general least squares (estimator)
FX . . . Foreign exchange (rate)
GDP . . . Gross domestic product
GMM . . . General method of moments (estimator)
GVAR . . . Global vector autoregressive (model)
HH . . . Household
HQ . . . Hannan-Quinn (information criterion)
HRW . . . Hard red winter (wheat)
IFS . . . International Financial Statistics
IID . . . Identically and independently distributed
IMF . . . International Monetary Fund
IRF . . . Impulse response function

LEV . . . . . Leverage
LHS . . . . . Left hand side
LOGLIKE . . . . . Log-likelihood (function)
MS . . . . . Markov switching (process)
MSH-SVAR Markov switching in heteroskedasticity structural vector autoregressive (model)
MSH-VAR . . . . . Markov switching in heteroskedasticity vector autoregressive (model)
NFB . . . . . Non-financial business
NID . . . . . Normally and independently distributed
NPO . . . . . Non-profit organization
NYMEX . . . . . New York Mercantile Exchange
NYSE . . . . . New York Stock Exchange
OLS . . . . . Ordinary least squares (estimator)
PPP . . . . . Purchasing power parity
RBOB . . . . . Reformulated blendstock for oxygenate blending (gasoline)
RGDP . . . . . Real gross domestic product
ROA . . . . . Return on assets
S&P GSCI . . . . . Standard & Poor's Goldman Sachs Commodity Index
SC . . . . . Schwarz (information) criterion
SCOT . . . . . Supplemental Commitments of Traders (report)
SLOOS . . . . . Senior Loan Officer Opinion Survey (on Bank Lending Practices)
SRW . . . . . Soft red winter (wheat)
SVAR . . . . . Structural vector autoregessive (model) / Structural vector autoregression
TED . . . . . Treasury Bill Eurodollar Difference
U.K. . . . . . United Kingdom (of Great Britain and Northern Ireland)
U.S. . . . . . United States (of America)
USD . . . . . U.S. Dollar
VaR . . . . . Value-at-Risk
VAR . . . . . Vector autoregessive (model) / Vector autoregression
VARX . . . . . Vector autoregressive (model) with exogenous variable(s)
VIX . . . . . Chicago Board Options Exchange (CBOE) volatility index
VSTOXX . . . . . EURO STOXX 50 volatility index
WTI . . . . . West Texas Intermediate (oil)

Abbreviations of countries correspond to the three-letter ISO 3166-1 alpha-3 country codes.

Summary

The global financial crisis demonstrated the importance of financial frictions for asset pricing and business cycles and revived the interest in macrofinancial linkages. Financial frictions on the supply side can distort asset price dynamics and give rise to macrofinancial linkages running from the financial sector to the real economy. This supply channel places special emphasis on financial intermediaries, in particular on their balance sheet and resulting risk-bearing capacity and lending decisions. This thesis applies different classes of structural vector autoregressive (VAR) models to provide empirical findings on the role of financial intermediaries in financial markets and the macroeconomy. Financial intermediaries are at the center of this dissertation and the link among its four chapters. Chapter 1 and 2 study the influence of financial intermediaries on asset price dynamics in commodity futures markets. Chapter 3 and 4 analyze the consequences of loan supply reductions and, more generally, deleveraging by financial intermediaries for macroeconomic outcomes. The thesis employs state-of-the-art identification techniques of VAR models and also shows how multivariate structural time series models which are widely applied in empirical macroeconomics can be used to study questions in finance, too.

The first chapter, which is based on joint work with Malte Rieth and Anton Velinov, studies the state-dependent trading behavior of financial intermediaries in the oil futures market, using structural vector autoregressions with Markov switching in heteroskedasticity. The empirical model is identified through theory-implied restrictions and allows decomposing changes in futures price volatility across regimes into changes in the slopes of traders' demand curves and in the variability of their demand shocks. We find that the downward-sloping demand curve of intermediaries steepens significantly during turbulent times, which amplifies the price impact of other traders' demand shocks by almost two thirds. Moreover, the variance of intermediaries' own demand shocks doubles during these episodes, further raising price volatility. These findings suggest that the futures pricing of intermediaries is nonlinear and increases the hedging costs of producers and processors of oil when volatility is high.

The second chapter, resulting from collaboration with Malte Rieth, proposes a simple econometric framework for structurally estimating the trading strategies of different trader groups in a given asset market and the implications for asset price volatility. We model each group's demand function depending on the contemporaneous asset price and a group-specific demand shock within a system of simultaneous equations. We apply the methodology to commodity futures markets, using two different publicly available datasets. We document that most trader groups employ contrarian strategies. They decrease net long exposure when prices rise, providing liquidity to other traders and stabilizing prices. In contrast, money managers and non-commercials follow momentum strategies, consuming liquidity when prices increase and raising volatility.

Chapter 3 provides empirical evidence on the effects of business and household loan supply shocks for the U.S. macroeconomy. Theoretically predicted differences in their macroeconomic implications as well as varying dynamics call for a joint but disaggregated analysis of loan supply shocks in one structural model. Results from a VAR model identified by combining sign and zero restrictions show that both loan supply shocks mainly operate through a quantitative channel. While the effect of both loan supply shocks on real GDP as well as on employment is similar on impact, household loan supply shocks are longer lasting and have a larger cumulative effect. Investigating the impulse response of several other macroeconomic variables reveals differences in their effects on the real economy and suggests that household loan supply shocks resemble classical demand shocks. Overall, both loan supply shocks have contributed significantly to business cycle dynamics over the sample period.

In the last chapter, I propose an approach to study the global effects of European bank deleveraging, using a structural times series model featuring international spillovers. Running a panel regression of leverage ratios of large European banks on macro-financial conditions and bank-specific factors allows obtaining an external instrument of unexplained shifts in their leverage ratio. I then employ the instrument to identify an exogenous shock to the balance sheet of European banks that induces them to adjust their leverage. The impact of the identified shock is studied in a global vector autoregressive model encompassing 30 advanced and emerging economies over the time period 1999Q1 to 2016Q4. The results suggest that European bank balance sheet shocks significantly affect gross capital inflows and real credit growth, in particular in advanced economies with developed financial markets, but have only minor effects on real output growth in the majority of countries.

Keywords: Financial intermediaries, Asset pricing, Trading behavior, Loan supply shocks, European banks, Business cycle, Global financial cycle, Structural VAR, Global VAR, Sign restrictions, Zero restrictions, External instrument, Markov switching, State-dependency, Commodities, Futures markets, Liquidity, Contrarian traders, Momentum traders, Business loans, Household loans, Credit, Leverage, Deleveraging, Balance sheet.

JEL Classification: C32, E32, E44, E51, F34, F36, F44, G12, G21, Q02.

Zusammenfassung

Die globale Finanzkrise unterstrich die Bedeutung von Finanzfriktionen für die Preisbildung auf Vermögensmärkten und Konjunkturschwankungen und erneuerte das Interesse an makrofinanziellen Verknüpfungen. Angebotsseitige Finanzfriktionen können Vermögenspreisdynamiken verzerren und zu makrofinanziellen Verknüpfungen führen, welche vom Finanzsektor zu der Realwirtschaft verlaufen. Dieser Angebotskanal misst vor allem Finanzintermediären eine wichtige Rolle zu, insbesondere ihrer Bilanz und der daraus resultierenden Risikotragfähigkeit und den Kreditvergabeent- scheidungen. Diese Dissertation wendet verschiedene Klassen von strukturellen vektorautoregressiven (VAR) Modellen an um empirische Belege für die Rolle von Finanzintermediäre für Finanzmärkte und die Gesamtwirtschaft zu liefern. Finanzintermediäre stehen im Mittelpunkt dieser Dissertation und stellen die Verknüpfung zwischen den vier Kapiteln dar. Kapitel 1 und 2 untersuchen den Einfluss von Finanzintermediären auf Vermögenspreisdynamiken in Rohstoff-Futures-Märkten. Kapitel 3 und 4 analysieren die gesamtwirtschaftlichen Konsequenzen einer Verminderung des Kreditangebots durch Finanzintermediäre sowie eines Schuldenabbaus von Finanzintermediären im Allgemeinen. Die Dissertation verwendet neueste Identifizierungsmethoden für VAR Modelle und zeigt zudem wie multivariate strukturelle Zeitreihenmodelle, welche in der empirischen Makroökonomie weit verbreitet sind, auch für Fragen der Finanzökonomie herangezogen werden können.

Das erste Kapitel, das auf einer gemeinsamen Arbeit mit Malte Rieth und Anton Velinov beruht, untersucht das regimeabhängige Handelsverhalten von Finanzintermediären auf dem Öl-Futures-Markt unter Verwendung eines strukturellen vektorautoregressiven Modells mit Markov-Switching in Heteroskedastizität. Das empirische Modell ist durch theoriebasierte Restriktionen identifiziert und ermöglicht die Zerlegung von Veränderungen in der Preisvolatilität der Futures zwischen den Regimen in Veränderungen in der Steigung der Nachfragekurven der Händler und in die Varianz ihrer Nachfrageschocks. Die Ergebnisse zeigen, dass die abwärts geneigte Nachfragekurve von Finanzintermediären signifikant steiler wird in turbulenten Zeiten, was die Preiseffekte von Nachfrageschocks anderer Händler um nahezu zwei Drittel erhöht. Außerdem verdoppelt sich die Varianz der eigenen Nachfrageschocks der Intermediäre während diesen Perioden, was eine weitere Steigung der Preisvolatilität bedingt. Diese Ergebnisse deuten auf eine nichtlineare Futurespreissetzung von Intermediären hin, welche die Hedgingkosten von Öl-Produzenten und Öl-Verarbeitern in Zeiten hoher Volatilität erhöhen.

Das zweite Kapitel, welches in Zusammenarbeit mit Malte Rieth entstanden ist, führt ein einfaches ökonometrisches Modell ein um die Handelsstrategien verschiedener Händlergruppen in einem Vermögensmarkt sowie deren Auswirkungen für die Vermögenspreisvolatilität strukturell zu schätzen. Wir modellieren die Nachfragekurve jeder Händlergruppe in Abhängigkeit von kontemporären Preis und einem gruppenspezifischen Nachfrageschock innerhalb eines Systems simultaner Gleichungen. Folgend wenden wir die Methode auf Rohstoff-Futures-Märkte an, unter

Verwendung von verschiedenen öffentlich verfügbaren Datensätzen. Die Ergebnisse dokumentieren, dass die meisten Händlergruppen eine antizyklische Investitionsstrategie verfolgen. Sie verringern ihre Netto-Long-Position wenn Preise steigen und stellen anderen Händlern Liquidität zur Verfügung und stabilisieren dadurch Preise. Money Manager und nicht-kommerzielle Händler setzen dagegen Momentumstrategien ein und konsumieren Liquidität wenn Preise steigen und erhöhen dadurch die Volatilität.

Kapitel 3 präsentiert empirische Belege über die Effekte von sektorspezifischen Kreditangebotsschocks gegenüber Firmen einerseits und Haushalten andererseits für die US-amerikanische Makroökonomie. In der Theorie vorausgesagte Unterschiede in den makroökonomischen Implikationen als auch unterschiedliche Dynamiken verlangen nach einer gemeinsamen aber disaggregierten Analyse von Kreditangebotsschocks in einem strukturierten Modell. Ergebnisse eines mittel einer Kombination von Vorzeichen- und Null-Restriktionen identifizierten VAR Modells zeigen, dass beide Kreditangebotsschocks hauptsächlich über einen quantitativen Kanal wirken. Während der Effekt beider Kreditangebotsschocks auf das reale Bruttoinlandsprodukt als auch auf Beschäftigung beim Eintritt des Schocks ähnlich ist, sind Kreditangebotsschocks gegenüber Haushalten langlebiger und haben einen größeren kumulativen Effekt. Impuls-Antworten verschiedener anderer makroökonomischer Variablen weisen auf Unterschiede in den realwirtschaftlichen Effekten hin und zeigen, dass Kreditangebotsschocks gegenüber Haushalten klassischen Nachfrageschocks ähneln. Insgesamt haben beide Kreditangebotsschocks signifikant zum Konjunkturverlauf während des Beobachtungszeitraums beigetragen.

Im letzten Kapitel demonstriere ich eine Methode zur Analyse der globalen Auswirkungen des Schuldenabbaus europäischer Banken mittels eines strukturierten Zeitreihenmodells mit internationalen Übertragungseffekten. Eine Panelschätzung des Verschuldungsgrads großer europäischer Banken auf makrofinanzielle Bedingungen und bankspezifische Faktoren ermöglicht die Konstruktion eines externen Instrumentes von unerklärten Veränderungen im Verschuldungsgrad. Folgend verwende ich das Instrument um einen exogenen Bilanzschock auf europäische Banken zu identifizieren, welcher eine Anpassung des Verschuldungsgrads herbeiführt. Die Auswirkungen des identifizierten Schocks werden in einem globalen VAR Modell mit 30 fortgeschrittenen und entwickelnden Ökonomien in der Periode von 1999Q1 bis 2016Q4 untersucht. Die Ergebnisse weisen darauf hin, dass europäische Bankbilanzschocks Bruttokapitalflüsse und das reale Kreditwachstum signifikant beeinflussen, vor allem in fortgeschrittenen Ökonomien mit entwickelten Finanzmärkten, aber nur geringfügige Effekte auf das reale Wirtschaftswachstum in der Mehrheit der Länder haben.

Schlagworte: Finanzintermediäre, Vermögenspreisbildung, Handelsverhalten, Kreditangebotsschocks, Europäische Banken, Konjunkturschwankungen, Globaler Finanzzyklus, Strukturelles VAR, Globales VAR, Vorzeichenrestriktionen, Nullrestriktionen, Externes Instrument, Markov Switching, Regimeabhängigkeit, Rohstoffe, Futures-Märkte, Liquidität, Antizyklische Händler,

Momentumhändler, Firmenkredit, Haushaltskredit, Verschuldungsgrad, Schuldenabbau, Bilanz.

JEL Klassifikation: C32, E32, E44, E51, F34, F36, F44, G12, G21, Q02.

Introduction and Overview

By now ten years have passed since the bankruptcy of Lehman Brothers, which marked the peak of the global financial crisis and resulted in the Great Recession. The crisis once again demonstrated the importance of financial frictions for asset pricing and business cycles and revived the interest in macrofinancial linkages, especially in the role played by financial intermediaries. Research on macrofinancial linkages dates at least back to the Great Depression. For example, Fisher (1933) illustrates in his "Debt-Deflation Theory" how falling prices via rising real debt and declining net worth causes borrowers to default on their loans, which in turn adversely affects banks. However, in the following decades the research focus shifted and led to a separation of macroeconomics and finance.[1] On the one hand, macroeconomic research concentrated on the real side of the economy (see for example Lucas, 1975, Kydland and Prescott, 1982) and debated about the relevance of money, paying little attention to the financial sector and financial variables. The triumph of the rational expectations paradigm (Muth, 1961, Lucas, 1976) was associated with a focus on mostly frictionless models with fully optimizing agents. The financial sector was perceived as a "veil" to the real economy. The rise of vector autoregressive (VAR) models (Sims, 1972, 1980) contributed to view money as a key aggregate, but did not change the fundamental split between macroeconomics and finance.

On the other hand, this separation was also reinforced by prominent results in finance like most notably the "irrelevance of the financing structure" theorem by Modigliani and Miller (1958), which broadly interpreted suggests that real economic activity is independent from financial intermediation. Advances in asset pricing (Merton, 1973) and derivatives modeling (Black and Scholes, 1973) paved the way for the "efficient market hypothesis" (Fama, 1970, 1991) which ascribed virtually no role to financial intermediaries. Exceptions like the seminal work of Tobin (1969) who demonstrated how valuation of assets affects the investment of a firm or Diamond and Dybvig (1983) who presented the primary model of bank runs remained silent about financial intermediation and financial market imperfections. Contributions that studied the emergence of financial vulnerabilities (Minsky, 1982, 1986) and more general financial crises (Kindleberger, 1978) were largely of a qualitative nature and did not become central in macroeconomic research.

While the fundamental separation between macroeconomics and finance persisted, starting in the 1980s the idea of financial frictions gained in importance. Regarding finance, behavioral finance (Shiller, 1981, De Bondt and Thaler, 1985) started as a distinct field of research and laid the foundation for studying various frictions in financial markets and its implications for asset pricing (Shleifer and Vishny, 1997, Kyle and Xiong, 2001, Gromb and Vayanos, 2002, among others). Macroeconomic research saw the development of general equilibrium models that incorporated linkages running from the real economy to the financial sector. A series of papers,

[1] Claessens and Kose (2018) provide an extensive review on the literature on macrofinancial linkages, including a historical overview on which this introduction draws. See Brunnermeier et al. (2013) for an analytical survey on the literature on macroeconomic models with financial frictions.

most notably Bernanke and Gertler (1989), Bernanke et al. (1996), Carlstrom and Fuerst (1997), Kiyotaki and Moore (1997), and Bernanke et al. (1999), introduced the "financial accelerator" that describes how a fall in a firm's net worth worsens its ability to borrow, which adversely affects economic activity and amplifies the initial fall in asset prices. However, this kind of financial friction manifests itself through the demand side of credit, with financial intermediaries limited to propagate and amplify shocks originating in other sectors of the economy. Despite contributions pointing to the relevance of financial factors during the Great Depression (Mishkin, 1978, Bernanke, 1983) and static models on the role of bank capital (Hölmstrom and Tirole, 1997), it required the global financial crisis to fully acknowledge that financial frictions on the supply side can distort asset price dynamics and give rise to macrofinancial linkages running from the financial sector to the real economy. This supply channel places special emphasis on financial intermediaries, in particular on their balance sheet and resulting risk-bearing capacity and lending decisions.

In the area of finance, seminal papers by Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013) show theoretically how asset price dynamics may change during crises in markets where intermediaries are the marginal investors. Under financial stress, intermediaries' funding constraints can become binding and their risk-bearing capacity may shrink, which can lay the foundation for nonlinearities in the performance of asset markets and give rise to liquidity dry-ups and volatility spikes.[2] In macroeconomics, several theoretical contributions have extended the standard New Keynesian dynamic stochastic general equilibrium (DSGE) model by introducing an explicit financial intermediary sector. Prominent examples include inter alia Christiano et al. (2010), Cúrdia and Woodford (2010), Gerali et al. (2010), Gertler and Kiyotaki (2010), Gertler and Karadi (2011) and Brunnermeier and Sannikov (2014). These models feature financial intermediaries that drive a wedge between borrowers and lenders and usually incorporate both demand and supply types of macrofinancial linkages. Typically, banks transmit financial shocks to the real sector of the economy by curtailing their supply of loans to firms who then have to cut back investment. Regarding empirical studies, one strand of literature aims to identify bank capital or, more generally, credit supply shocks and to assess their impact on the real economy (Hristov et al., 2012, Bassett et al., 2014, Eickmeier and Ng, 2015, Gambetti and Musso, 2017, Furlanetto et al., forthcoming, among others).

Motivated by these recent papers, this thesis applies different classes of structural vector autoregressive (VAR) models to provide empirical findings on the role of financial intermediaries in financial markets and the macroeconomy. Financial intermediaries are at the center of this dissertation and the link among its four chapters. Chapter 1 and 2 study the influence of

[2] Based on these theoretical insights, several empirical papers have emerged that study the relation between asset prices and a variety of measures of intermediaries' financial health. Adrian et al. (2010) document that aggregate balance sheet figures of financial intermediaries contain strong predictive power for excess returns and Adrian et al. (2014) establish a relationship between the marginal value of intermediaries' wealth and asset returns. He et al. (2017) find that intermediaries act as marginal investors in many asset markets and findings of Muir (2017) suggest that the health of the financial sector is crucial to understanding risk premia.

financial intermediaries on asset price dynamics in commodity futures markets. Specifically, the first chapter focuses on the oil futures market and uses a nonlinear model to reveal differences in the trading behavior of financial intermediaries between tranquil times and volatile periods when their capital constraint becomes binding and their risk-bearing capacity shrinks. Chapter 2 broadens the perspective and studies the trading behavior and strategies of different trader groups in several commodity futures markets as well as its implications for market outcomes. The influx of financial intermediaries into commodity futures markets in recent decades has changed significantly price discovery and risk sharing among different trader groups in the markets (Cheng and Xiong, 2014). Chapter 3 and 4 analyze the consequences of loan supply reductions and, more generally, deleveraging by financial intermediaries for macroeconomic outcomes. The third chapter examines the impact of a reduction in the supply of loans separately for businesses and households on the U.S. macroeconomy in one structural VAR model. The last chapter investigates the global effects of deleveraging of large European banks who are key actors in the global financial system and have crucially shaped global financial conditions in the last two decades (Shin, 2012, Cerutti et al., 2017).

From a methodological point of view, the dissertation covers different classes of VAR models, which are identified by state-of-the-art identification techniques. Chapter 1 employs a nonlinear VAR model identified by theory-implied restrictions and additionally uses heteroskedasticity in the data to distinguish between two states of the world. Chapter 2 and Chapter 3 are based on linear VAR models with constant coefficients, the former identified through theory and the latter by combining sign and zero restrictions. The last chapter applies a self-constructed external instrument to identify a VAR model featuring cross-country spillovers, namely a global VAR (GVAR) model. The first two chapters also demonstrate how multivariate structural time series models which are widely applied in empirical macroeconomics can be easily employed to study questions in finance, too. In the following, the four chapters and their contributions to the literature are briefly summarized.

The **first chapter**, *Nonlinear Intermediary Pricing in the Oil Futures Market*, which is joint with Malte Rieth and Anton Velinov, analyzes the state-dependent trading behavior of financial intermediaries in the oil futures market and the associated implications for price dynamics. We start by formulating a stylized conceptual framework for the oil futures market following Cheng et al. (2015). It describes the trading behavior of different trader groups in terms of simple net long demand curves depending on the contemporaneous futures price and a group-specific demand shock. The framework provides sufficient restrictions for the just-identification of the empirical counterpart, which is a Markov switching in heteroskedasticity structural vector autoregressive (MSH-SVAR) model. We employ weekly position data from the U.S. Commodity Futures Trading Commission (CFTC) for the period 2006-2016 and consider two states of the world, tranquil and volatile periods. The endogenous determination of these states is at the core of the analysis. The Markov switching framework allows us to be agnostic about the state determination and gives full voice to the data (Hamilton, 1994). The model allows switching of both the impact effects and the volatility of the structural shocks across states. Thereby, we can decompose changes in futures price volatility into changes in the slopes of traders' demand curves and in the volatility of their demand shocks. This flexibility enables us to jointly test our two main hypotheses: (1) are financial intermediaries less willing or able to absorb trades of other market participants, such as producers or processors of oil, during turbulent times and (2) do they trade more according to their own demand during these episodes? More formally, we test whether their demand is less price-elastic and whether the volatility of their demand shocks increases during certain periods.

The chapter contributes to the literature along several dimensions. The results show that the trading behavior of financial intermediaries changes significantly across states. First, the demand curve of intermediaries steepens significantly when switching from the tranquil to the turbulent state. The lower price elasticity implies that they are less willing or able to absorb trades of other groups. This increases the price effect of futures demand shocks by almost two thirds according to the estimates. Second, the variance of intermediaries' own demand shocks nearly doubles during these episodes, further raising volatility. A possible interpretation for the latter finding is that intermediaries react more to shocks to their balance sheet during phases of financial market stress. Both findings are consistent with the theoretically predicted nonlinearities in Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013) and contribute to the understanding of the influence of intermediaries on the functioning of asset markets.

The study also relates to a long-standing literature on the determination of commodity futures prices and in particularly adds to the more recent debate whether financial investors affect commodity prices (Cheng and Xiong, 2014, Kilian and Murphy, 2014, Singleton, 2014, Hamilton and Wu, 2015, Henderson et al., 2015, Sockin and Xiong, 2015). Our results indicate that intermediaries in the oil futures market affect prices in a nonlinear way and that this increases the hedging costs of producers and processors of oil in high volatility regimes. The findings further support the notion of a "convective risk flow" (Cheng et al., 2015) from financial investors to hedgers during crises as hedgers end up holding more risk in these periods than otherwise.

Methodologically, the chapter combines the type of Markov switching models following Herwartz and Lütkepohl (2014) with the framework of Bacchiocchi and Fanelli (2015). The first model type determines regime switches endogenously, but allows only for changes in the volatility of the structural shocks across regimes. The second class allows for changes in both the contemporaneous effects and the volatility of the structural shocks, but defines the regimes exogenously based on prior information. Our model contains both desirable features: an endogenous regime determination, and changes in the impacts and in volatility. This is crucial for our analysis as it allows, first, endogenously estimating when significant changes in volatility occur and, second, decomposing them into changes in the slopes of demand curves and into changes in the volatility of demand shocks.

The **second chapter**, *An Empirical Characterization of Commodity Futures Trading*, based on joint work with Malte Rieth, proposes a simple econometric framework for structurally estimating the trading strategies of different trader groups in a given asset market. Building on the theoretical model of chapter 1, we represent each group's net long demand curve depending on the contemporaneous asset price and a group-specific demand shock within a system of simultaneous equations. The multivariate empirical model, which is identified through theory, allows to quantify the price and liquidity effects due to traders' trading decisions and captures two main trading motives of traders: liquidity provision following endogenous price movements and trading for own purposes based on exogenous private signals. We apply the methodology to several commodity futures markets, using two different publicly available datasets from the U.S. CFTC which differ in their classification of traders. As stated above, the increased presence of financial traders has changed the functioning of commodity markets (Cheng and Xiong, 2014, Basak and Pavlova, 2016, Chari and Christiano, 2017), which has also questioned long-standing traditional views like the theory of normal backwardation (Keynes, 1930, Hicks, 1939) and its generalization through the hedging-pressure theory (Hirshleifer, 1990). The growing evidence points towards financial traders pursuing own investment strategies and trading objectives which are independent of meeting producers' hedging demands (Moskowitz et al., 2012, Rouwenhorst and Tang, 2012, Kang et al., 2017). We document that most trader groups, including producers and swap dealers, employ contrarian strategies. They decrease their net long exposure when prices rise, providing liquidity to other traders and stabilizing prices. However, swap dealers who are mostly large banks trading on behalf of their clients or on their own behalf experience themselves periods in which they restrict liquidity provision, in particular during times associated with general financial market turmoil (Cheng et al., 2015). In contrast, non-commerical traders and, more specifically, money managers follow momentum strategies and increase their net long exposure when prices rise, thereby consuming liquidity in the market and raising price volatility. The associated price effects and the demand for liquidity is comparatively small, though.

The second chapter contributes to a better understanding on how different market participants, in particular financial traders, in commodity futures markets affect price dynamics and liquidity through their specific trading behavior. This is crucial for understanding the functioning of the market as a whole as well as regarding its design. In contrast to commonly employed single equation models in empirical finance where identification is typically achieved via lead lag relationships, our framework makes use of VAR models that have been developed to address problems of simultaneity. It can enhance single equation models where identification is typically achieved via lead-lag relationships along two dimensions. First, it allows modeling contemporaneous relationships between prices and positions. This is particularly relevant given the development of financial markets with electronic and algorithmic trading where market participants respond to price developments in essentially continuous time. Our results show that most of the responses occur indeed contemporaneously, implying that models which use a lag structure for identification miss the largest part of it. Second, the approach facilitates a decomposition of observed price dynamics into the contributions of different trader groups and their trading behavior. While we study commodity futures markets, our framework is by no means specific to it and can be straightforwardly applied to any asset market with at least three trader groups. The model is very flexible and can easily be extended to include more trader groups and as we show also control for common shocks that potentially influence the behavior of all market participants. For instance, the framework could be applied to investigate empirically the trading behavior and liquidity provision of market makers in different asset markets (Grossman and Miller, 1988, Campbell et al., 1993, Weill, 2007, Nagel, 2012).

The **third chapter**, *Macroeconomic Effects of Loan Supply Shocks: Distinguishing Between Business and Household Loans*, studies the impact of business and household loan supply shocks on the U.S. economy and reveals some significant differences in their macroeconomic effects and overall importance in driving business cycles. The empirical analysis is accomplished by applying a structural VAR model that is identified by combining sign and zero restrictions using the recent algorithm of Arias et al. (2018) and spans the period 1980Q1 to 2016Q4. Besides a baseline model consisting of seven variables, I estimate a couple of extended model versions in which I include an eighth variable to study the macroeconomic transmission mechanisms of the two loan supply shocks. The main results of the analysis show that both loan supply shocks mainly operate through a quantitative channel, that is, they have a strong and prolonged effect on the corresponding loan volume, but almost none on the loan rate at the short horizon. The effect of business and household loan supply shocks on real GDP as well as on employment is similar in the first quarters after the shock impact, but household loan supply shocks are more persistent and thus have a larger cumulative effect. Household loan supply shocks further appear to resemble classical demand shocks since they depress inflation, provoke an easing of monetary policy, and also affect business loans over time. Moreover, they exhibit a significantly negative impact on consumption and marginally negative one on real house prices and investment. They also lead to a rise in the private saving rate at medium horizons. Business loan supply shocks, on the other hand, have a quite short-lived impact on investment and also marginal effects on consumption and net exports-to-GDP around one quarter after the shock has hit. They further slightly affect the volume of corporate bonds in the short term as firms with access to capital markets seem to be able to substitute loans with corporate bonds at least partly. Finally, forecast error variance decompositions and a historical decomposition reveal that both loan supply shocks have contributed significantly to business cycle dynamics over the sample period, especially during the during the Great Recession following the global financial crisis. Overall, the analysis shows the crucial role of household loans for the U.S. macroeconomy and substantiates theoretical and empirical studies alike that stress the importance of household finance for the economy (Mian and Sufi, 2010b, 2011, Eggertsson and Krugman, 2012, Mian et al., 2013, Guerrieri and Lorenzoni, 2017, Mian et al., 2017, Jones et al., 2018). Having said this, results from sensitivity analyses suggest that in case of household loan supply shocks it is the drop in home mortgages during the global financial crisis that seems to be a main driver behind these findings.

This chapter contributes to the literature by providing the first structural time series analysis that isolates business and household loan supply shocks from each other in one structural model and assesses their macroeconomic effects and differences in them. Despite being studied in some recent contributions (Hristov et al., 2012, Bassett et al., 2014, Bijsterbosch and Falagiarda, 2015, Duchi and Elbourne, 2016, Gambetti and Musso, 2017, among others) and broad consensus on their general macroeconomic relevance, there remain open questions about their transmission mechanisms to the real economy and whether there are differences depending on which sector is affected. The majority of empirical contributions so far - be it microeconometric or macroeconometric - has either focused on lending to the whole private non-financial sector or solely on one sector. Consequently, all these papers discard information on differences in the dynamics of business and household loans and neglect potentially important spillover effects between firms and households (Caggese and Pérez-Orive, 2016). Moreover, they cannot make a statement on potential differences in the transmission mechanisms to the real economy as well as on the relative importance of business versus household loan supply shocks in driving the business cycle.

The **fourth chapter**, *Global European Banks and the Global Financial Cycle*, proposes a simple approach to study the global effects of European bank deleveraging within a structural times series model featuring international spillovers. In a first step, I run a panel regression on the leverage ratio of large European banks to partial out country-specific and global macro-financial conditions as well as bank-individual factors. Aggregating the estimated bank-individual residuals allows constructing an exogenous time-series measure of fundamentally unexplained shifts in the leverage of large European banks that serves as a proxy for supply-side bank balance sheet shocks. Intuitively, the shock can be interpreted either as an exogenous change in a bank's ability to raise funding in the market, or in a bank's risk assessment owing to alterations in its own perception of risk and monitoring incentives or due to regulatory requirements. Both scenarios affect a bank's leverage as well as potentially, but not necessarily, its supply of credit. In a next step, I apply the proxy as an external instrument to identify a structural European bank balance sheet shock (Stock and Watson, 2012, Mertens and Ravn, 2013) in a global vector autoregressive (GVAR) model consisting of 30 advanced and emerging economies over the period 1999Q1 to 2016Q4. In focusing on the effects of variables associated with the global financial cycle (Rey, 2013), I consider two specifications of the GVAR model, one including gross capital inflows and one real credit growth. The results suggest that European bank balance sheet shocks significantly affect gross capital inflows and real credit growth, but have only minor effects on real output growth in the majority of countries and geographical regions. Looking at aggregated country groups, advanced economies which are financially developed and open are generally more affected than emerging market economies with less developed and less open financial markets. In contrast, the sheer number of European banks present in a country seems to be of subordinate importance.

The last chapter contributes to the literature by analyzing international spillovers of structural shocks to the balance sheet of large European banks to advanced and emerging economies within a GVAR model. European banks are key actors in the global financial system and have played an important role for global financial conditions (Acharya and Schnabl, 2010, Shin, 2012, Ivashina et al., 2015, Cerutti et al., 2017) and sophisticated finance areas like trade or project finance (Feyen and del Mazo, 2013) in the last two decades. Given these observations, assessing international spillovers of (de-)leveraging of European banks not only contributes to the understanding of the global financial crisis and the global financial cycle (Rey, 2013), but it is moreover of interest to policymakers and regulators. Related works either limit their analysis to Europe (Gross et al., 2016, 2017) or study a general sign-identified credit supply shock (Eickmeier and Ng, 2011, Fadejeva et al., 2015), thereby ignoring the possibility of different ways of how banks can adjust their leverage and how their supply of credit is affected by this across different countries (Giannetti and Laeven, 2012a,b). Second, building on previous works by Hancock and Wilcox (1993, 1994), Berrospide and Edge (2010), Mésonnier and Stevanovic (2012), Bassett et al. (2014), and Altavilla et al. (2015), the paper demonstrates a way of constructing an external instrument to identify a structural supply-side balance sheet shock to large European banks. Instead of utilizing bank capital measures or lending survey data, I use bank-individual leverage ratios as leverage has been found to be the main indicator of a bank's ability to grant credit (Adrian and Shin, 2010), is closely related to a simple Value-at-Risk (VaR) rule that targets a constant probability of default (Adrian and Shin, 2014) and is a main determinant of cross-border transmission of financial conditions via capital flows (Bruno and Shin, 2015b). Third, from a methodological point of view the paper is among the first to apply the external instrument identification method (Stock and Watson, 2012, Mertens and Ravn, 2013) to GVAR models.

CHAPTER 1

Nonlinear Intermediary Pricing in the Oil Futures Market[1]

1.1 Introduction

Traditional theories of asset pricing assign no role to financial intermediaries and view them as a veil without influence on the functioning of financial markets. This conjecture has been questioned. Modern finance theories state that intermediaries, broadly defined as entities which channel funds between different parties, affect asset prices due to several frictions (Shleifer and Vishny, 1997, Kyle and Xiong, 2001). Following the global financial crisis, Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013) show theoretically how asset price dynamics may change during crises in markets where intermediaries are the marginal investors. Under financial stress, intermediaries' funding constraints can become binding and their risk-bearing capacity may shrink. Such occasionally binding constraints lay the foundation for nonlinearities in the performance of asset markets and can give rise to liquidity dry-ups and volatility spikes.

Based on these theoretical insights, several empirical papers study the relation between asset prices and a variety of measures of intermediaries' financial health. Adrian et al. (2014) document a relationship between the marginal value of intermediaries' wealth and asset returns. He et al. (2017) find that intermediaries act as marginal investors in many asset markets. Focusing on commodity markets, Acharya et al. (2013) show that the severity of intermediaries' capital constraints affects futures risk premia, and Etula (2013) highlights the relevance of the risk-bearing capacity of securities broker-dealers for futures risk premia.

These empirical findings support theoretical arguments that the risk and trading constraints of financial institutions are time-varying and change through volatility regimes. They further suggest that such nonlinearities are key to understand commodity futures markets and, given an arbitrage relation, potentially also spot prices. What is missing in the literature, however, is an analysis of the state-dependent trading behavior of financial intermediaries and the associated implications for price dynamics. We aim to fill this gap by building a Markov switching in heteroskedasticity structural vector autoregressive (MSH-SVAR) model for the oil futures market, using weekly position data from the U.S. Commodity Futures Trading Commission (CFTC) for the period 2006-2016. We focus on oil as the large exposure of banks to the oil sector has raised concerns about financial stability (Domanski et al., 2015).

[1] This chapter is based on joint work with Malte Rieth and Anton Velinov.

We use a stylized conceptual framework following Cheng et al. (2015). It describes the trading behavior of different trader groups in terms of simple net long demand curves depending on the contemporaneous futures price and a group-specific demand shock. The framework provides sufficient restrictions for the just-identification of the structural empirical model. The main identifying assumption is that traders do not directly respond to position changes of other trader groups. This assumption is consistent with a publication lag of the CFTC data and the electronic trading at the New York Mercantile Exchange to which the data refer, making aggregate position changes of other trader groups contemporaneously unobservable. We consider two states of the world: tranquil and volatile periods. The endogenous determination of these states is at the core of the analysis.

Our paper contributes to the literature along several dimensions. The results show that the trading behavior of financial intermediaries changes significantly across states. First, the demand curve of intermediaries steepens significantly when switching from the tranquil to the turbulent state. The lower price elasticity implies that they are less willing or able to absorb trades of other groups. This increases the price effect of futures demand shocks by two thirds according to our estimates. Second, the variance of intermediaries' own demand shocks doubles during these episodes, further raising price volatility.

Both findings are consistent with the theoretically predicted nonlinearities in Brunnermeier and Pedersen (2009) and He and Krishnamurthy (2013). The steeping of the demand curve is also in line with the empirical results of Cheng et al. (2015) who show that during, but not outside, the financial crisis higher option-implied stock market volatility was associated with a reduction in the long positions of financial traders, an increase in the long exposure of hedgers, and lower futures prices. This pattern is consistent with a time-varying risk sensitivity of financial investors and them initiating the trades during the crisis. Our estimates provide a structural identification and quantification of this effect and determine the crisis regime endogenously. The Markov switching framework allows us to be agnostic and give full voice to the data (Hamilton, 1994), thereby reducing the risk of misspecification of the transition points, variable(s), or functions. Since the structural model is just-identified for each state, we can let both the impact effects and the volatility of the structural shocks switch across states. This facilitates a decomposition of changes in futures price volatility into changes in the slopes of traders' demand curves and in the volatility of their demand shocks.

Our study also relates to a long-standing literature on the determination of commodity futures prices, and their relation to spot prices.[2] Recently, there has been much interest in the role of financial institutions in these markets and whether the increased presence of financial investors has changed the functioning of commodity markets (Fattouh et al., 2013, Cheng and Xiong, 2014). Our analysis focuses on the role of financial intermediaries in the price formation process

[2] See Garbade and Silber (1983), Hirshleifer (1990), Kilian and Murphy (2014), Hamilton and Wu (2015), Henderson et al. (2015), Sockin and Xiong (2015), Knittel and Pindyck (2016).

in the oil futures market. We show that their trading behavior is state-dependent and that this increases the hedging costs of producers and processors of oil in high volatility regimes.

The paper builds on a literature on structural time-series models with heteroskedasticity (Rigobon, 2003). We combine the type of Markov switching models following Herwartz and Lütkepohl (2014) with the framework of Bacchiocchi and Fanelli (2015). The first model type determines regime switches endogenously, but allows only for changes in the volatility of the structural shocks across regimes. The second class allows for changes in both the contemporaneous effects and the volatility of the structural shocks, but defines the regimes exogenously based on prior information. Our model contains both desirable features: an endogenous regime determination, and changes in the impacts and in volatility. This is crucial for our analysis as it allows, first, endogenously estimating when significant changes in volatility occur and, second, decomposing them into changes in the slopes of demand curves and into changes in the volatility of demand shocks. Another important difference to the aforementioned models is that we do not use the heteroskedasticity in the data for identification. The latter is achieved through economic reasoning, implying that our identified structural shocks have the simple economic interpretation as net long demand shocks of the trader groups included in the model. A clear advantage of this model over traditional linear SVAR models is that it can incorporate nonlinearities through its endogenously determined states. The model is also easily interpretable, in that, conditional on the state, the model is identical to a single state model.

Our results are robust to a large number of sensitivity tests. We also compare them with estimates from popular alternative classes of nonlinear models – threshold and smooth transition models – based on a single transition variable (Kilian and Lütkepohl, 2017, Ch. 18). These models yield similar conclusions regarding the state-dependent trading behavior of financial intermediaries. Furthermore, they show that the choice of the transition variable plays an important role in determining the model outcomes, that none of the exogenously determined states captures both the general financial market turmoil periods and the oil-market-specific events that the Markov switching model detects, and that the structural parameters are less precisely estimated across states. Finally, we investigate whether combinations of variables can capture the Markov switching regimes. We relate the smoothed probability of the high volatility state to model-external variables through logit regressions. They show that higher Baa-Aaa corporate bond spreads and lower U.S. Treasury yields are the best indicators of turbulent times, consistent with risk premia and risk-free rates being important factors for the futures basis and hence for futures price dynamics (Acharya et al., 2013, Szymanowska et al., 2014).

The remainder of the chapter is structured as follows. The next section discusses the literature on intermediary asset pricing, presents a simple conceptual framework and some testable implications. It further outlines the empirical methodology and describes the data. Section 1.3 contains the main results, while Section 1.4 compares them to other modeling approaches and provides further evidence on the characteristics of the high volatility state. This section also contains an extensive sensitivity analysis. The last section concludes.

1.2 Conceptual Framework, Empirical Model and Data

In this section, we first summarize the literature on intermediary asset pricing. Using the findings in the literature, we present a conceptual framework and derive two testable implications for the trading behavior of intermediaries in the oil futures market. The section ends with a description of the data.

1.2.1 Conceptual Framework

Traditional theories of asset pricing regard financial intermediaries as a veil without influence on the performance of asset markets. Intermediaries act according to their clients' preferences, making a representative household the marginal investor. This neglect of the intermediary sector has been questioned by numerous studies showing that intermediaries face a variety of constraints, such as limits to arbitrage, due to which they influence the functioning of asset markets (Shleifer and Vishny, 1997, Kyle and Xiong, 2001, Gromb and Vayanos, 2002, Fostel and Geanakoplos, 2008). In an influential paper Brunnermeier and Pedersen (2009) show the interdependence between the ability of intermediaries to raise capital and market liquidity. If funding liquidity is scarce, intermediaries are reluctant to open new positions, market liquidity is lower, and volatility is higher. He and Krishnamurthy (2013) study the asymmetric effects of intermediary capital on risk premia. When capital is abundant, intermediaries are able to offset losses such that there are only limited effects on risk premia. When capital is scarce, however, losses in the intermediary sector can be associated with higher and more volatile risk premia.

The subsequent empirical literature has studied the relation between intermediaries' financial health, using a variety of approximations of this unobservable variable, and asset prices. Adrian et al. (2014) investigate the relation between a stochastic discount factor based on the leverage of security broker-dealers and asset returns. He et al. (2017) use capital ratios of intermediaries and provide evidence that intermediaries are the marginal investors in many asset markets and thus key to understanding price formation. Focusing on commodity markets, Acharya et al. (2013) show that the futures risk premium and hence producers' hedging costs are increasing in the severity of intermediaries' capital constraints, measured by their assets relative to households' assets. Etula (2013) uses the leverage of securities broker-dealers, who serve as counterparties to hedgers, to build a risk aversion index and finds that it is a determinant of risk premia in commodity futures markets. Finally, Cheng et al. (2015) approximate the risk absorption capacity of financial traders in commodity futures markets with the VIX and document a risk transfer from those traders to hedgers during periods of high volatility.

These contributions suggest that when volatility is high (i) intermediaries are more reluctant to take on new positions, and (ii) their exposure to idiosyncratic balance sheet shocks increases. To map these considerations into testable implications, we formulate a stylized model of the oil futures market, following Cheng et al. (2015). The framework describes the trading behavior of all market participants, who are assumed to be atomistic price takers. We distinguish between three groups of traders: hedgers (H), financial intermediaries (F), and others (O). Hedgers are producers, processors, or large consumers of oil, who want to hedge physical oil price risk of commercial businesses. For the second group, we primarily think of it as large banks that either trade on behalf of clients without direct access to the futures market or on their own behalf. The third group contains all remaining traders and is mainly comprised of specialized commodity trading advisors, commodity pool operators, and traders who cannot be clearly classified in any other category. The demand curves of the three trader groups are

$$\begin{aligned}
\Delta y^H &= -a^H(S)\Delta P + \sqrt{\lambda^H(S)}\nu^H \\
\Delta y^F &= -a^F(S)\Delta P + \sqrt{\lambda^F(S)}\nu^F \\
\Delta y^O &= -a^O(S)\Delta P + \sqrt{\lambda^O(S)}\nu^O,
\end{aligned}$$

where Δy^i denotes the change in the net long oil futures position of trader group $i = H, F, O$. ΔP is the change in the oil futures price. The coefficients $a^i(S)$ determine the slope of the respective demand curve and thus measure the price elasticity of each group. They reflect the capacity or willingness to absorb trades of other groups. Illiquidity might arise if there are limits to arbitrage which deter risk averse arbitrageurs from taking the counter-side. Shleifer and Summers (1990) and Shleifer and Vishny (1997), for example, show that large position changes can influence prices through an effect on the order book if the instantaneous supply of counterparty orders is low. Regarding financial intermediaries, a smaller value of a^F implies that they absorb a smaller part of the desired demand shift of producers and processors or, equivalently, provide less liquidity, and that the price impact will be larger.

Each demand curve further features a random shock ν^i which causes the respective trader group to adjust its net long position due to own reasons. For financial intermediaries the causes can be manifold: portfolio diversification, risk management, speculative motives based on private signals, or long hedging of short exposure vis-à-vis clients. The $\lambda^i(S)$'s measure the variances of the shocks and are allowed to differ across groups. One can interpret these coefficients as the exposure of each trader group to its idiosyncratic shocks. For example, if we think of ν^F as a shock hitting the balance sheet of intermediaries, then a larger λ^F suggests a greater exposure to this shock. Although being highly stylized, the simple demand functions thus capture two main trading motives of financial institutions in commodity futures markets: liquidity provision to other traders and trading for own purposes. The usual market clearing condition, $\Delta y^H + \Delta y^F + \Delta y^O = 0$, closes the model and ensures that the price is jointly determined by all trader groups in equilibrium.

We distinguish in an ad-hoc form between two different states $S = 1, 2$ of the world. Without loss of generality, we think of state 1 as tranquil periods and of state 2 as volatile times. The latter can be either episodes of general financial market turmoil that spill over to the oil futures market through balance sheets of intermediaries or drastic oil market developments that directly affect intermediaries in the oil futures market. The central feature of the model is that the $a^i(S)$ and $\lambda^i(S)$ coefficients are allowed to differ between regimes. Hence, both the ability of traders to absorb other traders' shocks as well as the variance of own shocks can change between states. Using the market clearing condition and writing the system in matrix notation gives

$$\begin{pmatrix} 1 & 0 & a^H(S) \\ 0 & 1 & a^F(S) \\ -1 & -1 & a^O(S) \end{pmatrix} \begin{pmatrix} \Delta y^H \\ \Delta y^F \\ \Delta P \end{pmatrix} = \begin{pmatrix} \sqrt{\lambda^H(S)}\nu^H \\ \sqrt{\lambda^F(S)}\nu^F \\ \sqrt{\lambda^O(S)}\nu^O \end{pmatrix}. \tag{1.1}$$

The inclusion of these endogenous variables allows us to capture the most relevant players in the oil futures market. Including an additional group "Other Reportables" as a robustness exercise does not influence our findings. Expression (1.1) is the basis for the identification of our structural empirical model. It illustrates our main identifying restrictions which are reflected in the zero elements on the LHS of (1.1). We assume that no trader group responds directly to the position change of any other group. This assumption is consistent with the publication lag of the CFTC data that we use and the market to which they refer. The positions correspond to each Tuesday end-of-day at the electronic trading platform of the New York Mercantile Exchange. Here, aggregated orders of the other investors are not observable. But the CFTC reports are released only the following Friday, implying that traders cannot contemporaneously observe and thus directly respond to aggregated position changes of other groups. They do so, of course, indirectly through prices.

Given the theoretical literature discussed above and to focus the empirical analysis, we now postulate the following two hypotheses about the changes in the coefficients across states:

Hypothesis 1 *The downward-sloping demand curve of financial intermediaries steepens during turbulent times:* $a^F(2) < a^F(1)$.

Hypothesis 2 *The volatility of intermediaries' demand shifts increases during turbulent times:* $\lambda^F(2) > \lambda^F(1)$.

The alternative hypotheses are that there are no significant changes across regimes, implying that there is no clear difference in the way financial intermediaries trade in tranquil versus turbulent times, or that the changes in parameters are significant but with the opposite sign. Finally, unlike Cheng et al. (2015), our framework does not contain a common shock which simultaneously affects all trader groups (potentially to differing degrees). This reduces the computational complexity of the estimation. Instead, we deal which such shocks by including a number of exogenous control variables in the baseline empirical model and by conducting an extensive sensitivity analysis adding further controls.

1.2.2 The MSH-SVAR Model

We now describe the general M state, p lag reduced form Markov switching in heteroskedasticity vector autoregressive (MSH-VAR) model:

$$y_t = c + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \Psi_0 x_t + \Psi_1 x_{t-1} + \cdots + \Psi_n x_{t-n} + u_t, \tag{1.2}$$

where in our case $y_t = [\Delta y_t^H, \Delta y_t^F, \Delta P_t]'$ is the vector of endogenous variables with Δy_t^H and Δy_t^F the change in the net long futures position of hedgers and financial intermediaries, respectively, and ΔP_t the oil futures return. Further, x_t is a vector of W exogenous variables discussed below, Γ_i and Ψ_j are parameter matrices with $i = 1, \ldots, p$ and $j = 1, \ldots, n$, where n does not necessarily equal p, and c is a vector of constants. Finally, u_t is a vector of reduced form error terms with $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[u_t u_t'] = \Sigma_u(S_t)$. For estimation purposes, we assume that u_t is normally and independently distributed conditional on a given state:

$$u_t | S_t \sim \mathrm{NID}(0, \Sigma_u(S_t)).$$

Here, S_t is a first order discrete valued Markov process that can take on M different values, $S_t = 1, \ldots, M$, with transition probabilities given by $p_{kl} = P(S_t = l | S_{t-1} = k), k, l = 1, \ldots, M$. Although the model is linear in a given state, it is nonlinear as a whole.

Using the conceptual model in (1.1), we write the structural empirical model as

$$\underbrace{\begin{bmatrix} 1 & 0 & a^H(S_t) \\ 0 & 1 & a^F(S_t) \\ -1 & -1 & a^O(S_t) \end{bmatrix}}_{\equiv A(S_t)} \underbrace{\begin{bmatrix} \Delta y_t^H \\ \Delta y_t^F \\ \Delta P \end{bmatrix}}_{=y_t} = \begin{bmatrix} \epsilon_t^H \\ \epsilon_t^F \\ \epsilon_t^O \end{bmatrix},$$

where $\epsilon_t = [\epsilon_t^H \ \epsilon_t^F \ \epsilon_t^O]'$ is a vector of structural shocks whose standard deviations correspond to $\sqrt{\lambda^i}$ in the conceptual model, and where we have neglected constants, lags and exogenous variables for illustration.[3] This leads to the following relationship between the reduced form errors and the structural shocks: $u_t = A(S_t)^{-1}\epsilon_t$, where $A(S_t)^{-1}$ is a matrix of state-dependent instantaneous effects.

It is important that despite the zeros in $A(S_t)$ all variables are allowed to react contemporaneously to all shocks since

$$A^{-1}(S_t) = \begin{bmatrix} \frac{a^F(S_t)+a^O(S_t)}{\tilde{a}(S_t)} & -\frac{a^H(S_t)}{\tilde{a}(S_t)} & -\frac{a^H(S_t)}{\tilde{a}(S_t)} \\ -\frac{a^F(S_t)}{\tilde{a}(S_t)} & \frac{a^H(S_t)+a^O(S_t)}{\tilde{a}(S_t)} & -\frac{a^F(S_t)}{\tilde{a}(S_t)} \\ \frac{1}{\tilde{a}(S_t)} & \frac{1}{\tilde{a}(S_t)} & \frac{1}{\tilde{a}(S_t)} \end{bmatrix}, \tag{1.3}$$

[3] Implicitly this means that $\nu^i \sim (0,1)$ and that $\epsilon^i \equiv \sqrt{\lambda^i(S)}\nu^i \sim (0, \lambda^i(S))$.

where $\tilde{a}(S_t) = a^H(S_t) + a^F(S_t) + a^O(S_t)$. This is a central feature of the model and a main building block of the empirical plausibility of our identifying assumptions as traders respond to each other through prices in nearly continuous time. Any zero restrictions on $A^{-1}(S_t)$ would thus be difficult to justify. The specific structure of $A^{-1}(S_t)$ follows from the restrictions placed on $A(S_t)$ and reveals that a change of $a^F(S_t)$ across states affects the response of all variables to all shocks as it enters the denominator of all elements in $A^{-1}(S_t)$.

In order to allow for state-dependence of the instantaneous effects we model $A(S_t)$ as

$$A(S_t) = \bar{A} + \mathcal{A}(S_t), \quad S_t = 1, \dots, M, \tag{1.4}$$

where $\bar{A}$ consists of the state-invariant part and $\mathcal{A}(S_t)$ is the state-dependent part of the matrix. For simplicity, we set $\mathcal{A}(1) = 0$. To summarize, the definitions are

$$A(S_t) = \begin{bmatrix} 1 & 0 & a^H(S_t) \\ 0 & 1 & a^F(S_t) \\ -1 & -1 & a^O(S_t) \end{bmatrix}, \quad \bar{A} = \begin{bmatrix} 1 & 0 & \bar{a}^H \\ 0 & 1 & \bar{a}^F \\ -1 & -1 & \bar{a}^O \end{bmatrix}, \quad \mathcal{A}(S_t) = \begin{bmatrix} 0 & 0 & \alpha^H(S_t) \\ 0 & 0 & \alpha^F(S_t) \\ 0 & 0 & \alpha^O(S_t) \end{bmatrix}. \tag{1.5}$$

Further, we assume that the structural errors have a non-identity diagonal covariance matrix: $E[\epsilon_t \epsilon_t'] = \Lambda(S_t)$ (naturally $E[\epsilon_t] = 0$). We allow this matrix to be state-dependent in an analogous fashion as above

$$\Lambda(S_t) = \bar{\Lambda} + \mathit{\Lambda}(S_t), \quad S_t = 1, \dots, M, \tag{1.6}$$

where each matrix is diagonal. The orthogonality of the structural errors is required for identification of the structural parameters and is reasonable for idiosyncratic shocks. We use a variety of endogenous control variables in order to control for any common shocks. A typical element of $\Lambda(S_t)$ is $\lambda^i(S_t) = \bar{\lambda}^i + \ell^i(S_t)$, where $\bar{\lambda}^i$ and $\ell^i(S_t)$ are the respective elements of $\bar{\Lambda}$ and $\mathit{\Lambda}(S_t)$. Again, for simplicity, we set $\mathit{\Lambda}(1) = 0$. The covariance matrix of the reduced form errors can then be written as

$$\Sigma_u(S_t) = A(S_t)^{-1} \Lambda(S_t) (A(S_t)^{-1})' \,. \tag{1.7}$$

The system contains six structural parameters per state. These can be directly mapped to the six unique reduced form parameters through (1.7). The model is thus just-identified for any M; due to restrictions based on economic reasoning, without relying on changes in volatility. This approach uses a combination of established approaches found in the literature. For instance, the decomposition in (1.7) is used by Lanne et al. (2010), Herwartz and Lütkepohl (2014) and others. In addition, analogous decompositions as in (1.4) and (1.6) can be found in Bacchiocchi and Fanelli (2015). While our approach does make use of existing techniques, unlike in the literature, we do not assume an identity covariance matrix for the structural shocks in the first state, that is, $\Lambda(1) \neq I$, and we use, in the terminology of Lütkepohl (2005, Ch. 9), an A-model for identification instead of a B-model, which is employed in the aforementioned papers.

Finally, the Markov switching model differs from models with exogenously determined regimes, such as threshold and smooth transition structural time series models in that it treats any potential transition variable(s) as latent. This allows the researcher to be more agnostic on the state determination. Section 1.4.1 compares our results with results from such models.

1.2.3 Estimation and Bootstrap Procedure

The parameters in (1.2) are estimated by means of the expectation maximization (EM) algorithm of Hamilton (1994, Ch. 22), which was extended to multivariate processes by Krolzig (1997). Crucial for the analysis is to incorporate the regime-switching nature of the covariance matrix described in (1.4) and (1.6), given the restrictions in (1.5). Note that the latter do not contain any sign restrictions on the coefficients $a^i(S)$. Following Podstawski and Velinov (2018), we use the following concentrated out log likelihood function in the maximization step of the EM algorithm:

$$\begin{aligned} l(\bar{A}, \mathcal{A}(2), \ldots, \mathcal{A}(M), \bar{\Lambda}, \mathit{\Lambda}(2), \ldots, \mathit{\Lambda}(M)) \;&=\; \frac{1}{2}\sum_{m=1}^{M}\Bigg[\widehat{T}_m \log(\det(\Sigma_u(m))) \\ &\quad + \operatorname{tr}\Bigg((\Sigma_u(m))^{-1}\sum_{t=1}^{T}\widehat{\xi}_{mt|T}\widehat{u}_t\widehat{u}_t'\Bigg)\Bigg], \end{aligned}$$

where $\Sigma_u(m)$ is defined as in (1.7). Further, $\xi_{mt|T}, m = 1, \ldots, M,\ t = 1, \ldots, T$ are the model smoothed probabilities, $T_m = \sum_{t=1}^{T}\xi_{mt|T}$, and the hat symbol denotes estimated parameters obtained from the previous iteration.

Once the EM algorithm has converged, we obtain standard errors of the point estimates of the parameters through the inverse of the negative Hessian matrix evaluated at the optimum. We use these standard errors as a first statistic to determine whether the estimated parameters change significantly across states. As a second statistic, we use Likelihood Ratio tests, where we restrict the main parameters of interest to be time-invariant. As a third statistic, we compute bootstrapped impulse responses. Given the heteroskedasticity, classical residual bootstrapping may be problematic in generating reliable confidence intervals. Any re-sampling scheme needs to preserve the second order characteristics of the data. We therefore use a fixed design wild bootstrap with $u_t^\star = \varphi_t\widehat{u}_t$, where φ_t is a random variable independent of y_t following a Rademacher distribution. That is, φ_t is either 1 or −1 with probability 0.5. This is a commonly used technique for these types of models (Herwartz and Lütkepohl, 2014, Podstawski and Velinov, 2018).

1.2.4 Data

We use data of the Disaggregated Commitments of Traders (DCOT) Report of the U.S. Commodity Futures Trading Commission (CFTC). The data are weekly and start from 13 June 2006 to May 24, 2016, thereby containing 520 observations. Due to data availability, we could not start our sample earlier. However, given the weekly frequency of the data, we have a good amount of observations to estimate our parameters precisely. We calculate the net long position of the trader groups denoted as "Producer/Merchant/Processor/User" and "Swap Dealer" in light sweet crude oil traded at the New York Mercantile Exchange (NYMEX) to approximate net long demand of hedgers and financial intermediaries, respectively. Given the computational complexity of the empirical model we focus on these two trader groups, as they have relatively well defined business models within classifications, and lump the remaining groups in the price equation. In Section 1.4.3, we show that the main results are insensitive to adding another trader group to the model. Regarding the oil futures price, we employ the next-to-maturity futures settlement price of light crude oil at NYMEX. All three endogenous variables enter the model in standardized first differences, or log differences in case of prices.

According to the definition of the CFTC, a swap dealer is "[a]n entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions" (CFTC, 2018a). The vast majority of them are major global banks and the remaining traders in this group are other banks and financial intermediaries (CFTC, 2018c). Heumesser and Staritz (2013) document that the four largest globally active banks in this category held around 70% of swap positions in commodity futures markets in 2008, namely, Goldman Sachs, Morgan Stanley, JP Morgan, and Barclays Bank. In 2012 the group was made up of Bank of America, JP Morgan, Goldman Sachs, and Citibank. Other banks with big swap positions include Merril Lynch, Deutsche Bank, HSBC, Credit Suisse, Rabobank, and UBS.

One caveat of the CFTC data are potential misclassifications of traders and hence reporting errors. First, financial intermediaries have incentives to be classified as hedgers since this entitles them to preferential treatments. Hedgers are exempted from position limits and face lower margins requirements, translating into less capital needed for maintaining open positions. Second, the data refer to total end-of-day positions of traders, meaning that positions are aggregated across trades due to different business reasons. This aggregation complicates an interpretation of position changes. Third, the CTFC itself changes the classification of traders from time to time, for example following alterations in the way traders participate in the futures market. Overall, misclassifications cannot be fully excluded. But the bias of these reporting errors is likely to imply that some financial traders are erroneously classified as hedgers and our results might then actually represent a lower bound of the influence of intermediaries on futures prices.

Finally, we augment the model with a number of contemporaneous exogenous variables to control for common factors that potentially affect positions of all trader groups simultaneously. We add the number of initial jobless claims to capture the state of the real economy and the balance sheet of the Fed to account for nominal developments. Both variables are available at the weekly frequency. Moreover, we include the surprise component in news releases of 30 U.S. macroeconomic indicators to account for public information approaching the market. In Section 1.4.3 we show that the results are insensitive to the inclusion of a large number of further exogenous variables. Appendix 1.A contains a complete description of the data used in the analysis.

1.3 Results

We start by showing statistical evidence supporting the choice of a regime-switching model, followed by a brief presentation of the endogenously determined states. We then discuss the model's main implications in terms of estimated structural parameters. Additionally, we report bootstrapped impulse responses and forecast error variance decompositions.

1.3.1 Model Selection

Table 1.1 shows two types of specification statistics for the Markov switching model.[4] The left panel shows lag selection criteria. We follow the literature and select the lag order of the endogenous variables in the MSH-VAR model based on a linear VAR model. All three information criteria point to one lag. This also seems plausible from an economic point of view, given that financial markets react immediately and adjust quickly to new information, and since our data are of weekly frequency. We use the same lag length for the exogenous variables.

The right panel shows that a MSH-VAR model is clearly preferred over a standard linear VAR according to the log-likelihoods and information criteria. The latter have been shown to work well to judge the performance of MS models (Psaradakis and Spagnolo, 2006), whereas standard tests are problematic for determining the number of states (Hansen, 1992). The choice of two states is motivated by theoretical reasoning (see Section 1.2). This number suffices to test our two hypotheses. Estimation of a two-state model is also less cumbersome and leads to more stable and precise estimates, given that a potential third state contains only a limited number of observations. Nevertheless, we consider a three state model in the robustness analysis.

Table 1.1: Model Specification Tests

	AIC	SC	HQ
Lag(s)	1	1	1

Note: Lag selection based on Akaike information criterion, Schwarz criterion, and Hannan-Quinn criterion.

Model	LogLike	AIC	SC
reduced form linear VAR	−2069.4	4354.7	4813.7
reduced form MSH-VAR, 2 states	−1957.2	4158.3	4676.8

Note: Model fit comparison of a linear VAR and a two-state MSH-VAR with lag order $n = p = 1$ based on the log-likelihood, Akaike information criterion, and Schwarz criterion.

1.3.2 Smoothed State Probabilities

One main feature of the Markov switching model is the endogenous determination of the two states based on changes in the reduced form covariance matrix. For the labeling of the states we

[4] In the Markov switching model only the covariance matrix is switching between the sates, the autoregressive coefficients and the intercept are state-independent. In Section 1.4.3, we estimate a model with changing intercept.

look at the diagonal elements of the reduced form covariance matrices:

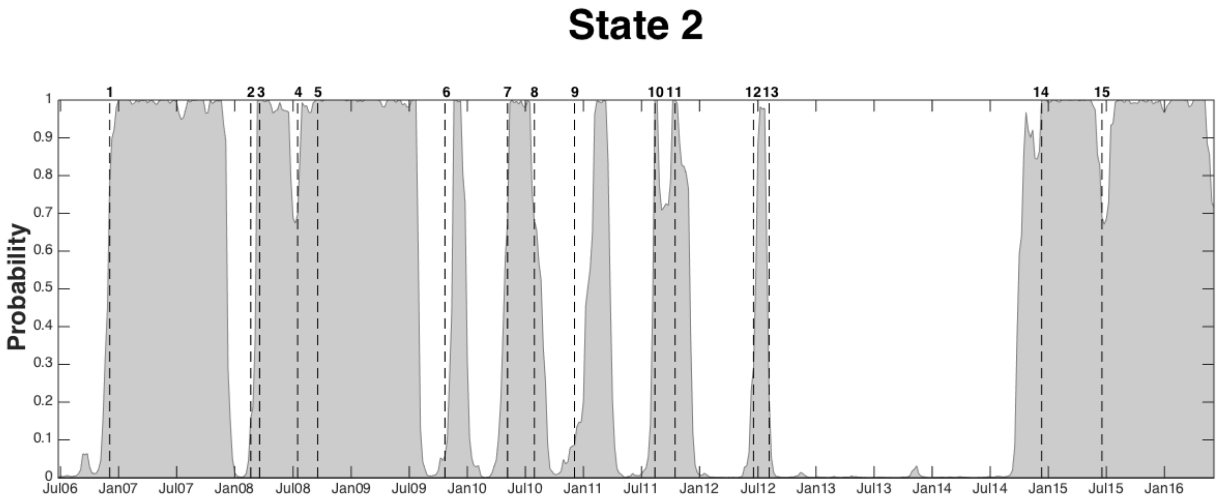
$$\Sigma_u(1) = \begin{pmatrix} 0.58 & \cdot & \cdot \\ 0.00 & 0.74 & \cdot \\ -0.11 & -0.33 & 0.31 \end{pmatrix} \qquad \Sigma_u(2) = \begin{pmatrix} 1.34 & \cdot & \cdot \\ -0.29 & 0.78 & \cdot \\ -0.23 & 0.05 & 1.58 \end{pmatrix}. \tag{1.8}$$

Equation (1.8) shows that there is a low-volatility regime, state 1, with relatively small variances, and a high-volatility regime, state 2, with larger variances. Especially the variance of the oil futures return increases strongly from 0.31 to 1.58 in state 2. The variance of net long positions of hedgers also more than doubles from 0.58 to 1.34. In contrast, the variance of net long positions of financial intermediaries increases only mildly from 0.74 to 0.78. Through the lens of the conceptual model, this modest change is likely reflecting two offsetting forces. On the one hand, a steeper demand curve of intermediaries (Hypothesis 1) means that they are less price-elastic and implies that a given order of other market participants induces a smaller change in intermediaries' positions and a larger price increase. On the other hand, a rise in the volatility of intermediaries' own demand shocks (Hypothesis 2) is tantamount to a rise in the variance of their positions. Together, we thus observe a small increase in the variance of intermediaries' positions and a large increase in the variance of the price in state 2. In the following we refer to state 1 as the "tranquil state" and to state 2 as the "turbulent state."

Figure 1.1 plots the smoothed probabilities of state 2. The dashed lines display a suggested selection of events that are likely to have had an effect on intermediaries in the oil futures market and potentially help rationalize the switches in the states. The switches occur both around events directly related to the oil futures market and during periods of more general financial market turmoil. In detail, we observe two longer phases in state 2 which coincide with oil market specific events. The first is towards the start of the sample. There was a boom in oil prices related to expectations of OPEC supply cuts. It is important to bear in mind that also short-selling requires capital in the form of margins. The second phase is at the end of the sample and is in line with the plunge in oil prices from late 2014 onwards. This episode also raised more general concerns about the health of financial institutions with a large exposure to the oil sector (Domanski et al., 2015), functioning as a common factor to which intermediaries reduce exposure across the board (Adrian et al., 2014).

There are also several periods where the switch to state 2 is concurrent with general market turmoil, as during the global financial crisis. The probability peaks for some months when concerns about the solvency of several large banks (Northern Rock and Bear Stearns) intensified. With the first actual failure of a big bank (IndyMac), the subsequent bankruptcy of Lehman Brothers, and the rescue of AIG, the model enters a prolonged phase in state 2 that lasts until summer 2009. It also generates increased probabilities surrounding important events of the euro area crisis, such as the Greek bailout in summer 2010, potentially reflecting both the exposure of U.S. banks to the euro area and the presence of European banks on U.S. futures markets (CFTC, 2018c). Another short switch to state 2 occurs between the second half of 2011, which

Figure 1.1: Smoothed Probabilities of State 2



1: OPEC president expects oil output cuts; 2: Northern Rock in state ownership; 3: Bear Stearns takeover bid; 4: IndyMac Bank failure; 5: Lehman Brothers failure & AIG rescue, OPEC production cutbacks; 6: Greece's budget deficit expected to reach ~12.5% of GDP; 7: Greece bailout; 8: Dodd-Frank-Act; 9: Ireland bailout; 10: USA downgrading; 11: FED UMP announcement, ECB Covered Bond Purchase Programme; 12: Bank bailout Spain; 13: OMT London; 14: OPEC keeps production target despite oversupply; 15: OPEC Meeting

Note: Plot of the endogenously estimated smoothed probabilities of the high volatility state 2, that is, the "turbulent state." Dashed lines correspond to selected events that are listed below the figure.

begins with the U.S. debt-ceiling crisis and the subsequent downgrading of the U.S. by Standard & Poor's, as well as the return of the euro area crisis. All in all, this narrative indicates that our agnostic model seems to identify a high volatility state not only for periods of stress in the oil market but also for crisis times in other financial markets. To investigate this issue further, we later study the relation of the smoothed probability with other asset prices.

1.3.3 State-Dependent Intermediary Pricing

In the following we formally test our two main hypotheses by evaluating the estimated parameters of interest, and their statistical significance based on the Hessian. We also perform Likelihood Ratio tests to compare the baseline specification allowing for switches in all parameters with alternative models which restrict the parameters of interest to be time-invariant.

We start with the estimated instantaneous relations between variables in the tranquil state:

$$A(1) = \bar{A} = \begin{pmatrix} 1 & 0 & \underset{(0.22)}{1.06^{***}} \\ 0 & 1 & \underset{(0.13)}{1.52^{***}} \\ -1 & -1 & \underset{(0.53)}{0.56} \end{pmatrix}.$$

The matrix corresponds to the one in the conceptual model so that we can interpret the estimated coefficients in the last column as the slope parameters of the demand curves of the three trader groups. Hedgers are ordered first, financial intermediaries second, and the group of others third. The values in parentheses show the standard errors. Asterisks indicate whether the parameters are different from zero ($*$, $**$, $***$ correspond to significance at the 10%, 5%, and 1% level, respectively). The estimated slopes for hedgers and financial intermediaries are highly statistically significant, with the latter demand curve being flatter. In tranquil times, intermediaries have the highest price elasticity and are the group most willing to take counterpositions. This ability shows how intermediaries facilitate hedging of producers and contribute to the functioning of the market. The slope parameter of others is not significant, potentially reflecting trader heterogeneity within this group.

To test Hypothesis 1, we evaluate $\mathcal{A}(2)$ which contains the changes in the slope coefficients when switching to state 2:

$$\mathcal{A}(2) = \begin{pmatrix} 0 & 0 & \underset{(0.28)}{-0.31} \\ 0 & 0 & \underset{(0.14)}{-1.26^{***}} \\ 0 & 0 & \underset{(0.60)}{0.41} \end{pmatrix}.$$

The only slope that changes significantly is the one for intermediaries. The change has the expected sign and is economically relevant. The demand curve steepens by more than 80%. Adding $\bar{A}$ and $\mathcal{A}(2)$ yields the slope coefficients in state 2:

$$A(2) = \bar{A} + \mathcal{A}(2) = \begin{pmatrix} 1 & 0 & 0.75 \\ 0 & 1 & 0.26 \\ -1 & -1 & 0.96 \end{pmatrix}.$$

Comparing the slope for intermediaries directly across regimes shows that $a^F(1) = 1.52 > 0.26 = a^F(2)$, or, equivalently, that $a^F(1) - a^F(2) = 1.26 > 0$. As this difference is statistically different from zero the estimates suggest that intermediaries absorb trades of other market participants to a lesser extent during turbulent times. This result lends support to the prediction of the theoretical literature that intermediary asset pricing is state-dependent, and shows that the oil futures market is a typical asset market. Moreover, together with the smoothed state probabilities it suggests that this market is not only affected by own developments but also by financial turmoil originating in other markets where financial intermediaries are active as well. Brunnermeier and Pedersen (2009) refer to this phenomenon as "commonality of liquidity across assets" which results from the difficulty of large banks to raise capital during periods of stress. As a result, market liquidity as a whole can decrease and observed price volatility increases.

To further judge the economic significance of the change in the demand functions, we interpret the overall contemporaneous effects of net long demand shocks in both states. They take into account all instantaneous feedback among positions and prices and are given by

$$A(1)^{-1} = \begin{pmatrix} 0.66 & -0.34 & -0.34 \\ -0.48 & 0.52 & -0.48 \\ 0.32 & 0.32 & 0.32 \end{pmatrix}, \qquad A(2)^{-1} = \begin{pmatrix} 0.62 & -0.38 & -0.38 \\ -0.13 & 0.87 & -0.13 \\ 0.51 & 0.51 & 0.51 \end{pmatrix}. \tag{1.9}$$

Each column shows the effects of a demand shock of a given trader group on the positions of hedgers and intermediaries, and on prices. Comparing the response of intermediaries' positions to demand shocks of the other two trader groups between state 1 and 2 shows that intermediaries absorb trades from other market participants to a lesser extent in the turbulent state. The respective value decreases in absolute terms from 0.48 to 0.13. Instead, intermediaries are mostly trading for own reasons, as indicated by the increase from 0.52 to 0.87 of the effect of their own shocks on own positions.

The bottom rows show that regardless of which trader groups' demand is shifting, the price impact in a given regime is the same as it depends on all traders' demand curves (see last rows in (1.3) and (1.9)). Across regimes, however, the price impact increases strongly, by nearly 60%. When interpreting this number, one has to bear in mind that the elements in $A(S)^{-1}$ are functions of all three estimated slopes in $A(S)$ and that some coefficients and their changes are not statistically significant. But when considering only the significant change in the coefficient for intermediaries, a^F, the price effect of demand shocks is 0.53, which is virtually the same as when considering all changes in slopes.[5] Hence, regardless of the precise computation, the price impact of any trade in the market increases by almost two thirds in state 2, and the results indicate that this is mostly due to a steeper demand curve of financial intermediaries.

To test Hypothesis 2, we turn to the estimated structural variances in state 1, $\Lambda(1)$, and their switch to state 2, $\Lambda(2)$:

$$\Lambda(1) = \bar{\Lambda} = \begin{pmatrix} \underset{(0.13)}{0.71^{***}} & 0 & 0 \\ 0 & \underset{(0.06)}{0.47^{***}} & 0 \\ 0 & 0 & \underset{(0.66)}{1.90^{***}} \end{pmatrix}, \qquad \Lambda(2) = \begin{pmatrix} \underset{(0.35)}{1.18^{***}} & 0 & 0 \\ 0 & \underset{(0.12)}{0.45^{***}} & 0 \\ 0 & 0 & \underset{(1.11)}{1.46} \end{pmatrix}.$$

All variances in state 1 are statistically significant. If we interpret the coefficient for intermediaries as their exposure to idiosyncratic balance sheet shocks, then intermediaries have the smallest reaction to own shocks in state 1. This finding is consistent with the idea that in normal times they can easily absorb ordinary balance sheet shocks. In state 2, however, the volatility

[5] In detail, the coefficients in the last row are given by $1/\tilde{a}(S_t)$, where $\tilde{a}(S_t) = a^H(S_t) + a^F(S_t) + a^O(S_t)$. Hence, $1/\tilde{a}(1) = 0.32$ and $1/\tilde{a}(2) = 0.51$. If we only change $a^F(S_t)$ between states, that is $\tilde{a}(2^*) = a^H(1) + a^F(2) + a^O(1)$, then we obtain $1/\tilde{a}(2^*) = 0.53$.

of demand shifts of intermediaries almost doubles from 0.47 to 0.92. Importantly, the change $\lambda^F(2) - \lambda^F(1) = 0.45 > 0$ is statistically significant at the one percent level. The estimates thus support Hypothesis 2 and suggest that during turbulent times the exposure of financial intermediaries to shocks hitting their balance sheet increases. Finally, the volatility of demand shocks of hedgers also changes significantly across regimes, being already relatively high in state 1. This finding suggests that producers and processors of oil have a large exposure to oil market specific shocks already during normal times, consistent with many items on their balance sheet being linked to the price of oil. This sensitivity increases further during episodes that contain large oil price swings.

Putting the results together, we calculate the overall impact of the different demand shocks on the endogenous variables. Using $\Lambda(2) = \bar{\Lambda} + \mathit{\Lambda}(2)$, they are given by

$$A(1)^{-1}\Lambda(1)^{0.5} = \begin{pmatrix} 0.56 & -0.23 & -0.47 \\ -0.41 & 0.35 & -0.67 \\ 0.27 & 0.22 & 0.44 \end{pmatrix}, \quad A(2)^{-1}\Lambda(2)^{0.5} = \begin{pmatrix} 0.85 & -0.36 & -0.70 \\ -0.18 & 0.83 & -0.24 \\ 0.69 & 0.49 & 0.93 \end{pmatrix}.$$

The numbers resemble those in (1.9) but provide additional insights as they take into account the size of demand shifts. While in state 1 intermediaries' positions are more driven by trades of other market participants than by own needs, this drastically changes during state 2, where intermediaries change positions predominantly in response to own shocks. Moreover, when taking into account the larger variances in state 2, the increase in the price impact of all demand shocks across regimes is even more pronounced. The price effects more than double in all cases.

Finally, we compare different model specifications through Likelihood Ratio tests as another means of analyzing the statistical properties of the main results. We compare the log-likelihood of the unrestricted baseline model, where all structural parameters are allowed to change across regimes, to three alternative restricted model variants, where some parameters are assumed to be time-invariant. We set either $\alpha^F(2) = 0$ (see 1.5), $\ell^F(2) = 0$ (see 1.6), or impose both restrictions simultaneously, that is, $\alpha^F(2) = \ell^F(2) = 0$. Table 1.2 shows that in all three cases the p-values of the tests are essentially zero, clearly rejecting the restrictions. We conclude that a model which allows for fully state-dependent trading behavior of intermediaries is favored by the data.

Table 1.2: Likelihood Ratio Tests of Restrictions for the MSH-SVAR Model

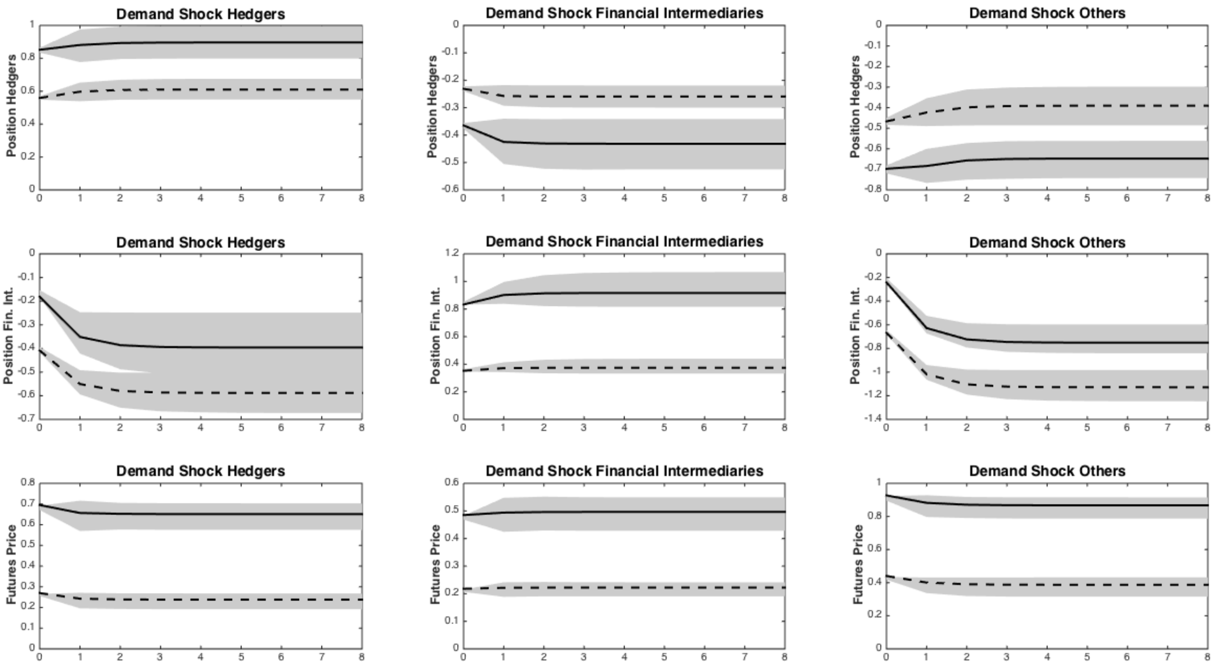
	H_1: baseline model specification	
$H_0 : \alpha^F(2) = 0$	$H_0 : \ell^F(2) = 0$	$H_0 : \alpha^F(2) = \ell^F(2) = 0$
1.11E-16	2.13E-04	0

Note: Likelihood Ratio tests comparing the baseline model specification (unrestricted model) with different alternative specifications in which parameters corresponding to financial intermediaries are set to zero (restricted model). Numbers represent p-values of the null hypothesis.

1.3.4 Impulse Responses and Forecast Error Variances

The matrices discussed so far show differences in the impact effects of the shocks across states. We now present impulse responses to assess the dynamic effects. The bootstrapped confidence intervals also provide a further alternative of testing whether the effects are significantly different across regimes, both upon impact and subsequently. Figure 1.2 shows the cumulative responses in both states.[6] The dashed line refers to the tranquil state and the solid line to the turbulent state. The shaded area displays 90% confidence intervals based on 1000 bootstrap replications. Overall, the figure corroborates the conclusions based on the impact effects. All responses are significantly different across regimes. In particular, the price effects of all three types of demand shocks are significantly larger in state 2. Moreover, we again find that financial intermediaries react stronger to their own shocks during turbulent times while absorbing less of the other traders' demand shocks. In contrast, hedgers react more to intermediaries' demand.

Figure 1.2: Cumulative Impulse Responses with 90% Bootstrapped Confidence Intervals



Note: Comparison of cumulative impulse responses of the three endogenous variables (in rows) to the three demand shocks (in columns) in state 1 (dashed line) and state 2 (solid line). Shaded areas represent 90% confidence intervals based on 1000 bootstrapped replications using a fixed design wild bootstrap. Vertical axes are in absolute changes in case of position variables and percentage changes in case of the futures price, horizontal axes are in weeks.

The figure also shows that the largest effects occur on impact with only a limited role for the dynamics, in particular of prices. This observation is in line with asset prices and financial market participants responding instantaneously to each other, and has several implications. First, it suggests that the estimates and the statistical inference based on the impact matrices capture

[6] The cumulative response for a given time horizon is the sum of all responses from the previous horizons until the current horizon. It therefore naturally stays persistent and is not expected to revert back to zero.

quantitatively most of the nonlinear effects of intermediary asset pricing. Second, it implies that other empirical approaches that are based on lead/lag relationships between variables for the identification of the impact of trading behavior on asset prices, or vice versa, are likely to miss a relevant fraction of the overall effects. Finally, technically, it means that the underlying assumption of no regime change over the impulse horizon is not crucial as most of the difference between regimes is on impact. Moreover, this assumption seems plausible for the chosen horizon of eight weeks as Figure 1.1 indicates a high persistence of each state. In fact, the probability of staying in the current state is 0.96 for both states.

As a final means of quantifying the importance of state-dependencies we compute forecast error variance decompositions. They yield the average regime-specific contribution of the structural shocks to the variability of the endogenous variables. We focus on the contributions of the shocks on impact which are similar to the decompositions for longer horizons. Table 1.3 shows that during tranquil times less than a fifth of the variability of intermediaries' positions is explained by own shocks. They mainly respond to demand shocks of hedgers and other traders. This is in stark contrast to the turbulent state, where nearly 90% of the variation in intermediaries' position is explained by own shocks. Each of the other two shocks contributes only about 5%. Interestingly, the importance of intermediaries' demand shocks for price fluctuations remains constant across regimes at 15%, despite a significant increase in the volatility of their demand shocks in state 2. This finding suggests that the main distinguishing feature of intermediaries relative to the other two trader groups is the significant decline in their price elasticity, which does not apply to the other two groups, rather than the increase in demand volatility in turbulent times, which is common to all three groups.

Table 1.3: Forecast Error Variance Decomposition

Variable	State	Demand Shock Hedgers	Demand Shock Fin.Int.	Demand Shock Others
Position Hedgers	1	0.54	0.09	0.37
	2	0.54	0.10	0.36
Position Financial Intermediaries	1	0.23	0.17	0.60
	2	0.04	0.88	0.07
Futures Price	1	0.23	0.15	0.62
	2	0.31	0.15	0.54

Note: Contribution of the three demand shocks to the forecast error variance of the endogenous variables upon impact in state 1 and state 2. The results change only marginally for longer horizons given that there is not much persistence in the first-differenced variables.

1.4 State Determination and Sensitivity Analysis

In this section, we first estimate exogenous switching models with a single transition variable to assess the sensitivity of our results and to compare them with estimates from those popular alternative classes of nonlinear models. We then investigate whether combinations of variables can be associated with the regimes identified by the Markov switching model through logit regressions on the smoothed probabilities. The section concludes with a series of robustness tests of the Markov switching model.

1.4.1 Exogenous Switching Models

Prominent examples of exogenous regime switching models are threshold and smooth transition SVARs. We estimate both types of models applying various transition variables, which reflect either general financial market or oil market conditions and are available at the weekly frequency. Following the literature we choose the VIX, the Baa-Aaa corporate bond spread, and the TED spread as measures of financial market conditions, and the realized volatility of the oil spot price as an oil market measure.[7] Table 1.4 shows that all variables correlate reasonably and with the expected sign with the probability of the high volatility state, but are far from identical to it.

Table 1.4: Correlations

	VIX	Baa-Aaa spread	TED spread	Realized volatility
State 2 prob.	0.36	0.40	0.36	0.49

Note: Correlations between smoothed state 2 probabilities and weekly financial variables. Variables are in levels. Sample period: June 27, 2006 to May 24, 2016. Number of observations: 518. See Table 1.8 in Appendix 1.A for a description of the variables.

In the threshold SVAR, the exogenous switching occurs when the transition variable s_t exceeds some certain threshold value at a specific observation date t. The threshold is typically chosen a priori and is often calibrated such that the model replicates some observed empirical pattern. We set it to be the 2/3-quantile, $q_s(2/3)$, of the transition variable over the whole sample period:

$$S_t = \begin{cases} 1 & \text{if } s_t \leq q_s(\frac{2}{3}), \\ 2 & \text{if } s_t > q_s(\frac{2}{3}). \end{cases}$$

This choice implies that the model dedicates 1/3 of the sample period to the turbulent state, roughly consistent with the 32% of observations in state 2 in the baseline MSH-SVAR model. Changing the threshold value to the 3/4-quantile affects the results only mildly.

[7] The VIX captures options-implied stock market volatility and is found to be linked to balance sheet constraints of intermediaries (Adrian and Shin, 2014). The Baa-Aaa spread is a commonly used indicator of credit spreads that signals default risk and possesses informational content for near-term economic growth (Gilchrist and Zakrajšek, 2012b). The TED spread, defined as the interest difference between three-month euro interbank deposits (LIBOR) and three-month U.S. Treasury bills, is an indicator of funding constraints and has been shown to correlate negatively with liquidity in the currency market (Mancini et al., 2013). The weekly realized variance is computed following Bollerslev et al. (2009) and we take the square root of it. As this measure is relatively noisy, we use the 8-week moving average of it as transition variable.

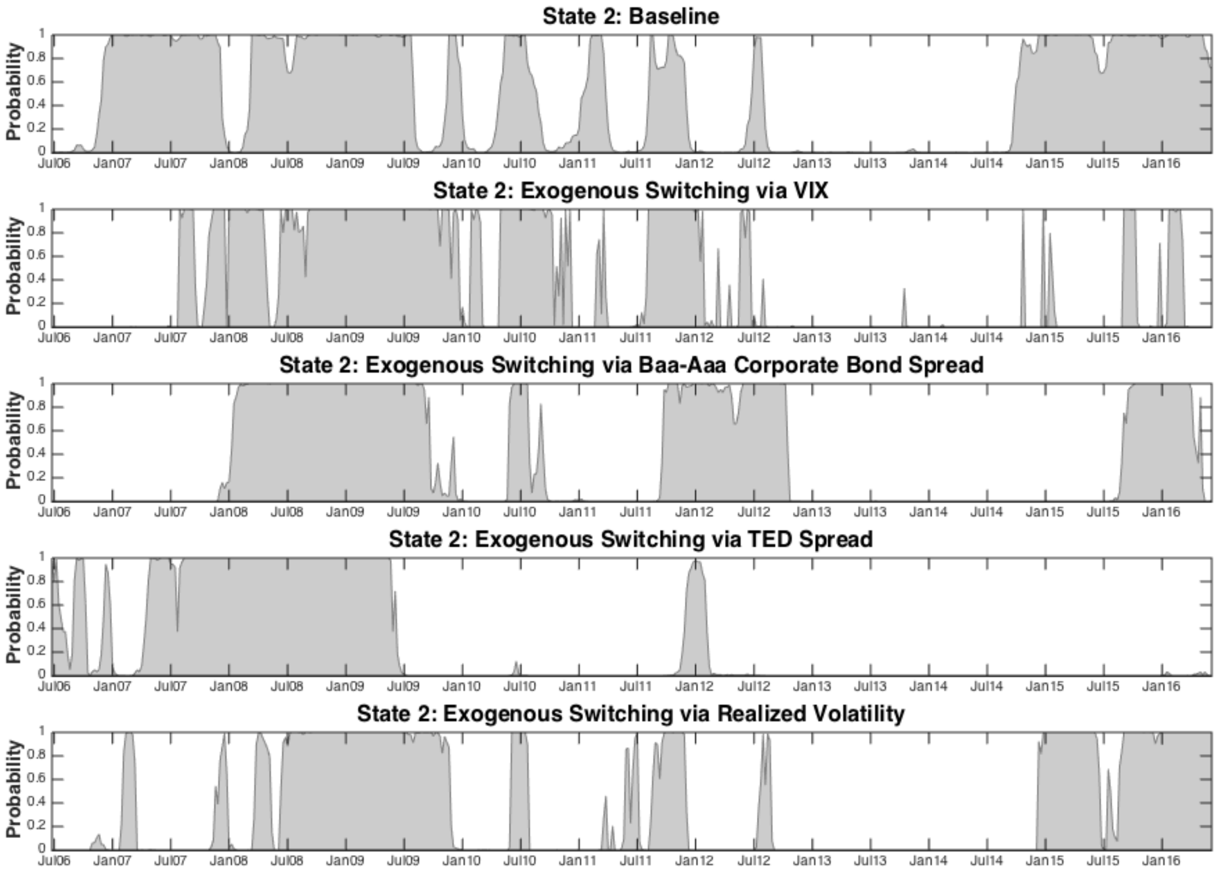
The smooth transition specification follows Kilian and Lütkepohl (2017, Ch. 18) and calculates the exogenous switching probabilities based on the following logistic function:

$$\begin{aligned} S_t(1) &= (1+\exp\{-\gamma(s_t-\mu)\})^{-1} \\ S_t(2) &= 1-S_t(1), \end{aligned}$$

where s_t denotes the transition variable, $\gamma > 0$ is a slope parameter determining the smoothness of the transition, and μ is a location parameter defining the midpoint of the transition. To avoid scaling issues we standardize the exogenous transition variables which allows us to leave the slope parameter constant across specifications. We set it to $\gamma = 25$, but our results are robust to using smaller or larger values. For the location parameter, we use the mean of the transition variable over the sample period for simplicity.

Figure 1.3 displays the exogenously identified states from the smooth transition models. No single transition variable captures both the episodes of general market turmoil and the oil-market-

Figure 1.3: Exogenous Smooth Transition Probabilities of State 2



Note: Comparison of the smoothed probabilities of the high volatility state 2, that is, the "turbulent state," between the baseline model and a model with exogenous switching. In the baseline model the smoothed probabilities are endogenously estimated, while in the model with exogenous switching the transition between the two states is determined by a logistic function of a specific transition variable (the VIX, the Baa-Aaa corporate bond spread, the TED spread, or the realized volatility of the oil spot price).

specific events that the MSH-SVAR model registers. When the VIX is used as a transition variable, the model partly misses oil-market-specific events, such as the strong oil price fluctuations in 2007 and towards the end of the sample. The Baa-Aaa spread based model, on the other hand, accounts for more of the later episode, but relatively late. Moreover, it seems to miss several of the spikes during the European debt crisis, probably reflecting that the transition variable refers to U.S. corporate bond yields. Similarly, the TED spread produces essentially transitions during the global financial crisis. Finally, the transition based on the realized oil price volatility tends to better capture both types of high volatility episodes, but partly neglects oil market events at the beginning of the sample and some switches during the European debt crisis. Moreover, the switches occur with some lag relative to the baseline model.

Table 1.5 contains the estimation results for both model types. Regardless of the specific transition variable, the estimated slopes of the demand curves are all highly significant in the tranquil state. In comparison to the baseline results, the slope for intermediaries is smaller in all cases but the change in the coefficient when switching to the turbulent state remains significant throughout. The variances of their demand shocks are all significant in the tranquil state, whereas the change in volatility to the turbulent state is only significant in some cases, and with the opposite sign. For all trader groups the volatility of demand shocks is considerably larger in the tranquil state, indicating that these models are less able to distinguish between different volatility regimes. The overall lower precision of the estimates is also reflected in a general loss of fit of these models relative to the Markov switching model. The latter yields higher log-likelihoods and is preferred according to both types of information criteria over any of the exogenous switching models (see second column). In summary, while the main results hold, the model fit deteriorates, the choice of the transition variable affects the results, and no single transition variable seems to recover the smoothed probabilities from the MSH-SVAR model. In the next section we therefore study whether a combination of variables can capture the smoothed probabilities.

1.4.2 Regression Analysis of State Probabilities

We relate the smoothed probabilities of state 2 of the MSH-SVAR model to a number of model-external variables through logit regressions.[8] This analysis can add to the economic interpretation of the agnostically identified regimes and potentially allows inferring which other markets are relevant for the trading of intermediaries in the oil futures market.

Since the smoothed probability is a continuous measure, we transform it into a dichotomous variable by assigning 1 whenever it is above 0.5, and 0 otherwise. Only 16% of the observations

[8] We choose a logit model for several reasons. First, standard OLS regressions seem inappropriate as the assumptions of linearity and homoskedasticity are violated. The smoothed probabilities show that many observations are close to 0 or 1, with only few observations with values in between. We opt for a logit model over a probit model as the former has fatter tails and is less sensitive to outliers. Probit regressions yield similar results, with the coefficients being smaller in absolute value as it is usually the case. Standard diagnostics tests like the link test for model adequacy or the Hosmer-Lemeshow test as well as inspecting the receiver operating characteristic curve indicate that the model is well specified.

Table 1.5: Comparison to other Model Classes

Alternative specification	LogLike/AIC/SC	$\rho\left(S_t(2)^{base.}, S_t(2)^{alt.}\right)$	$A(1) = \bar{A}$	$\mathcal{A}(2)$	$\Lambda(1) = \bar{\Lambda}$	$\mathit{\Lambda}(2)$
Baseline model	−1957.2 4158.3 4676.8	1.00	$\begin{pmatrix} 1 & 0 & 1.06^{***} \\ 0 & 1 & 1.52^{***} \\ -1 & -1 & 0.56 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.31 \\ 0 & 0 & -1.26^{***} \\ 0 & 0 & 0.41 \end{pmatrix}$	$\begin{pmatrix} 0.71^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 1.90^{***} \end{pmatrix}$	$\begin{pmatrix} 1.18^{***} & 0 & 0 \\ 0 & 0.45^{***} & 0 \\ 0 & 0 & 1.46 \end{pmatrix}$
Exogenous switching: VIX as threshold	−2029.2 4298.3 4808.3	0.28	$\begin{pmatrix} 1 & 0 & 0.97^{***} \\ 0 & 1 & 0.72^{***} \\ -1 & -1 & 1.51^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.50^{***} \\ 0 & 0 & -0.32^{**} \\ 0 & 0 & -0.54 \end{pmatrix}$	$\begin{pmatrix} 1.13^{***} & 0 & 0 \\ 0 & 0.85^{***} & 0 \\ 0 & 0 & 3.72^{***} \end{pmatrix}$	$\begin{pmatrix} 0.06 & 0 & 0 \\ 0 & 0.03 & 0 \\ 0 & 0 & -0.29 \end{pmatrix}$
Exogenous switching: Baa-Aaa spread as threshold	−2039.1 4318.3 4828.3	0.30	$\begin{pmatrix} 1 & 0 & 1.00^{***} \\ 0 & 1 & 0.70^{***} \\ -1 & -1 & 1.29^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.62^{***} \\ 0 & 0 & -0.34^{**} \\ 0 & 0 & -0.02 \end{pmatrix}$	$\begin{pmatrix} 1.42^{***} & 0 & 0 \\ 0 & 0.82^{***} & 0 \\ 0 & 0 & 3.43^{***} \end{pmatrix}$	$\begin{pmatrix} -0.66^{***} & 0 & 0 \\ 0 & 0.10 & 0 \\ 0 & 0 & 0.86 \end{pmatrix}$
Exogenous switching: TED spread as threshold	−2044.9 4329.9 4839.9	0.33	$\begin{pmatrix} 1 & 0 & 0.59^{***} \\ 0 & 1 & 0.68^{***} \\ -1 & -1 & 1.85^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.42^{*} \\ 0 & 0 & -0.40^{***} \\ 0 & 0 & -1.14^{*} \end{pmatrix}$	$\begin{pmatrix} 0.89^{***} & 0 & 0 \\ 0 & 0.91^{***} & 0 \\ 0 & 0 & 5.24^{***} \end{pmatrix}$	$\begin{pmatrix} 1.27^{**} & 0 & 0 \\ 0 & -0.23^{*} & 0 \\ 0 & 0 & -2.94 \end{pmatrix}$
Exogenous switching: realized oil price volatility as threshold	−1992.1 4224.2 4734.2	0.54	$\begin{pmatrix} 1 & 0 & 1.36^{***} \\ 0 & 1 & 0.98^{***} \\ -1 & -1 & 0.61^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -1.09^{***} \\ 0 & 0 & -0.73^{***} \\ 0 & 0 & 0.97 \end{pmatrix}$	$\begin{pmatrix} 1.30^{***} & 0 & 0 \\ 0 & 0.82^{***} & 0 \\ 0 & 0 & 2.14^{***} \end{pmatrix}$	$\begin{pmatrix} 0.31 & 0 & 0 \\ 0 & 0.05 & 0 \\ 0 & 0 & 4.03 \end{pmatrix}$
Exogenous switching: logistic function of VIX	−2028.7 4297.3 4807.3	0.31	$\begin{pmatrix} 1 & 0 & 1.00^{***} \\ 0 & 1 & 0.77^{***} \\ -1 & -1 & 1.39 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.53^{***} \\ 0 & 0 & -0.39^{***} \\ 0 & 0 & -0.21 \end{pmatrix}$	$\begin{pmatrix} 1.12^{***} & 0 & 0 \\ 0 & 0.90^{***} & 0 \\ 0 & 0 & 3.32^{***} \end{pmatrix}$	$\begin{pmatrix} 0.09 & 0 & 0 \\ 0 & -0.09 & 0 \\ 0 & 0 & 0.98 \end{pmatrix}$
Exogenous switching: logistic function of Baa-Aaa spread	−2034.7 4309.5 4819.5	0.31	$\begin{pmatrix} 1 & 0 & 1.07^{***} \\ 0 & 1 & 0.71^{***} \\ -1 & -1 & 1.22 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.72^{***} \\ 0 & 0 & -0.34^{**} \\ 0 & 0 & 0.29 \end{pmatrix}$	$\begin{pmatrix} 1.48^{***} & 0 & 0 \\ 0 & 0.81^{***} & 0 \\ 0 & 0 & 3.17^{***} \end{pmatrix}$	$\begin{pmatrix} -0.73^{***} & 0 & 0 \\ 0 & 0.09 & 0 \\ 0 & 0 & 2.34 \end{pmatrix}$
Exogenous switching: logistic function of TED spread	−2051.2 4342.4 4852.4	0.32	$\begin{pmatrix} 1 & 0 & 0.67^{***} \\ 0 & 1 & 0.67^{***} \\ -1 & -1 & 1.54^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.18 \\ 0 & 0 & -0.38^{***} \\ 0 & 0 & -0.73 \end{pmatrix}$	$\begin{pmatrix} 1.01^{***} & 0 & 0 \\ 0 & 0.93^{***} & 0 \\ 0 & 0 & 4.21^{***} \end{pmatrix}$	$\begin{pmatrix} 0.82^{*} & 0 & 0 \\ 0 & -0.29^{**} & 0 \\ 0 & 0 & -1.47 \end{pmatrix}$
Exogenous switching: logistic function of realized oil price volatility	−1984.0 4208.0 4718.0	0.59	$\begin{pmatrix} 1 & 0 & 1.43^{***} \\ 0 & 1 & 1.00^{***} \\ -1 & -1 & 0.57^{**} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -1.13^{***} \\ 0 & 0 & -0.72^{***} \\ 0 & 0 & 0.92 \end{pmatrix}$	$\begin{pmatrix} 1.30^{***} & 0 & 0 \\ 0 & 0.83^{***} & 0 \\ 0 & 0 & 2.10^{***} \end{pmatrix}$	$\begin{pmatrix} 0.30 & 0 & 0 \\ 0 & 0.04 & 0 \\ 0 & 0 & 3.37 \end{pmatrix}$

Note: The table shows the main results of models in which the transition between the tranquil and the turbulent state is determined exogenously, either according to a threshold or via a logistic function of a specific transition variable. The transition variables are the VIX, the Baa-Aaa corporate bond spread, the TED spread, and the realized volatility of the oil spot price. The first row contains the results for the baseline MSH-SVAR model. The second column reports the log-likelihood, the Akaike information criterion, and the Schwarz criterion. Column three states the correlation between the turbulent state of the baseline model and the respective exogenous switching model. The remaining columns display the matrix A of instantaneous relations among the endogenous variables and its switch $\mathcal{A}(2)$ to the turbulent state, as well as the variances of the identified demand shocks $\Lambda(1)$ and their switch $\mathit{\Lambda}(2)$ to the turbulent state. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively.

have a probability between 0.10 and 0.90, supporting this transformation. As regressors, we include a constant and, as suggested by the MS process, one lag of the original state probability. Given the high autocorrelation of the smoothed probabilities, this lag transforms the model essentially into a specification in first differences. We therefore use first (log) differences of the other regressors as well, which also reduces the risk of spurious regression. The regressors are the four variables employed as exogenous transition variable, the log S&P 500 index, the yield on ten-year U.S. Treasury bonds, a trade weighted U.S. Dollar index and the log oil spot price.

Table 1.6 shows the point estimates for the different variables, adding them one-by-one. Robust standard errors are in parentheses. The log odds for each variable has the expected sign and five out of the seven variables are significant. Increases in the VIX or the Baa-Aaa corporate bond spread signal higher uncertainty and reflect widening credit spreads, which are both signs of financial market stress. Increases in the S&P 500, in the ten-year rate, and the oil spot price, on the other hand, lower the probability of state 2. Lower equity or oil returns seem to have adverse effects on intermediaries' trading constraints. Together, the estimates support the conclusion from Figure 1.1 that the endogenously identified state 2 in the MSH-SVAR model reflects both oil and general financial market disturbances.

Table 1.6: Logit Regressions Baseline Results

Regressor	VIX	Baa-Aaa spread	TED spread	Realized volatility	S&P 500	Ten-year rate	Exchange rate	Oil price
Coefficient	0.19***	13.05***	0.95	11.34	−0.22*	−6.54***	0.46	−0.14**
Robust S.E.	(0.07)	(4.86)	(1.46)	(12.96)	(0.11)	(1.68)	(0.30)	(0.06)

Note: Logit models with dependent variable equal to 1 if probability of state 2 of MSH-SVAR model $\geq$ 0.5, and 0 otherwise. Explanatory variables are in first differences and include a lag of the endogenous variable and a constant. Pseudo $R^2 = 0.90$ in all models. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. Sample period: June 27, 2006 to May 24, 2016, weekly frequency, 517 observations. See Table 1.8 in Appendix 1.A for a description of the variables.

In Table 1.7 we add the same variables sequentially to the model. Only two variables remain significant: the Baa-Aaa spread and the ten-year Treasury rate. The negative coefficient on the Treasury rate is consistent with "flight to quality" phenomena (Brunnermeier and Pedersen, 2009) in state 2, induced by a commonality of liquidity across asset markets and resulting in declining yields. Both coefficients are also in line with risk premia and risk-free rates being important factors for the futures basis and hence for futures price dynamics (Acharya et al., 2013, Szymanowska et al., 2014).

1.4.3 Sensitivity Analysis

The section concludes with a number of robustness tests of the baseline MSH-SVAR model. First, we enlarge the baseline model by including another trader group, namely, the DCOT group of "Other Reportables." This group consists of reportable traders not classified as producers/processors/users, swap dealers, or money managers (see Appendix 1.A). Second, as in Herwartz and Lütkepohl (2014), we allow for a third volatility state. Appendix 1.B contains

Table 1.7: Logit Regressions Extended Models

Variable	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
VIX	0.19***	0.17**	0.19**	0.18*	0.27*	0.24	0.23	0.23
	(0.07)	(0.07)	(0.08)	(0.09)	(0.16)	(0.18)	(0.16)	(0.15)
Baa-Aaa spread		11.15**	11.60**	12.39**	14.20**	12.71**	11.65**	10.61*
		(5.28)	(5.16)	(5.35)	(5.73)	(5.68)	(5.93)	(6.07)
TED spread			−1.84	−1.83	−2.17	−2.47	−1.56	−1.25
			(1.67)	(1.81)	(1.64)	(1.83)	(2.39)	(2.57)
Realized volatility				8.26	10.90	7.76	7.85	8.79
				(10.78)	(12.11)	(11.58)	(11.11)	(10.61)
S&P 500					0.15	0.25	0.29	0.32
					(0.23)	(0.21)	(0.20)	(0.19)
10y TB rate						−5.48**	−6.05***	−5.70***
						(2.30)	(2.13)	(2.07)
Exchange rate							0.29	0.20
							(0.29)	(0.30)
Oil price								−0.07
								(0.08)
Observations	517	517	517	517	517	517	517	517
Pseudo R^2	0.90	0.90	0.90	0.90	0.91	0.91	0.91	0.91

Note: Logit models with dependent variable equal to 1 if probability of state 2 of MSH-SVAR model ≥ 0.5, and 0 otherwise. Explanatory variables are in first differences and include a lag of the endogenous variable and a constant. Robust standard errors are in parentheses. *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. Sample period: June 27, 2006 to May 24, 2016, weekly frequency. See Table 1.8 in Appendix 1.A for a description of the variables.

a figure with the smoothed probabilities for states 2 and 3. Third, we shorten the estimation period to June 12, 2007 until May 27, 2014 to exclude the large oil price swings at the beginning and end of the sample. Fourth, we allow for a more flexible specification with a switching intercept term. Fifth, we include all financial variables of Table 1.7 except the oil spot price in first (log-)differences as exogenous control variables in the model. Sixth, we exclude all exogenous variables from the model. Seventh, we estimate a model with four lags. Eighth, we allow for predetermined exogenous variables. Ninth, instead of using the log-change in the oil futures price, we employ the change in the oil futures-spot basis as a third variable besides the two position variables.

Table 1.9 in Appendix 1.B contains the key results of these alterations. They are qualitatively and mostly quantitatively similar to the baseline estimates, which are repeated in the first row for comparison. In all specifications the demand curve of financial intermediaries steepens significantly in the turbulent state, and the volatility of their own demand shocks is significantly larger. The endogenously identified states are similar across specifications and the correlation between the probability of state 2 in the baseline model and in alternative specifications is usually quite high (see second column).[9] Overall, the main results appear to be robust to the various alterations of the model and the data.

[9] One exception is the model with the futures basis, which is more volatile than the futures price. Further, the more volatile states 2 and 3 of the three-state model depict similar periods as state 2 in the baseline model, and would thus be jointly correlated with that state.

1.5 Conclusion

Modern asset pricing theories state that financial intermediaries face numerous frictions through which they affect the performance of financial markets. One of them is that during volatile times their trading constraints become binding and their risk-bearing capacity shrinks. Intermediaries may then be less able to enter new trades and may have to unwind existing positions. Such occasionally binding constraints lay the theoretical foundation for nonlinearities in the asset pricing of intermediaries (Brunnermeier and Pedersen, 2009, He and Krishnamurthy, 2013).

This paper contributes to the literature by building a Markov switching in heteroskedasticity structural vector autoregressive (MSH-SVAR) model that tests for the presence of such nonlinearities in the oil futures market. The model contains two endogenously identified states, one corresponding to low and one to high volatility. The empirical results suggest two central nonlinearities. First, the downward-sloping demand curve of intermediaries steepens significantly in the high volatility regime. The lower price elasticity implies that intermediaries accommodate given hedging needs of producers, processors and consumers of oil to a lesser extent, and that the price effect of these demand shocks increases strongly. Second, the volatility of intermediaries' own demand shocks increases significantly during these episodes. This raises futures price volatility further.

These findings indicate the existence and empirical relevance of the theoretically predicted state-dependency of intermediary asset pricing. Quantitatively, the estimates suggest that the steepening of the demand curve is the more important nonlinearity, and the main distinguishing feature of intermediaries relative to other trader groups in the oil futures market. Open questions are whether these nonlinearities are also present at lower frequencies and whether they help to explain the typically higher volatility of oil prices at high(er) frequencies.

1.A Data Appendix

Table 1.8: Definition of Variables

Variable	Definition and Source
Position Hedgers	Net long position of the trader group "Producer/Merchant/Processor/User" in light sweet crude oil traded at the New York Mercantile Exchange. Standardized first absolute differences. U.S. Commodity Futures Trading Commission (CFTC), Disaggregated Commitments of Traders (DCOT) Report.
Position Financial Intermediaries	Net long position of the trader group "Swap Dealer" in light sweet crude oil traded at the New York Mercantile Exchange. Standardized first absolute differences. U.S. Commodity Futures Trading Commission (CFTC), Disaggregated Commitments of Traders (DCOT) Report.
Futures Price	New York Mercantile Exchange light crude oil continuous futures settlement price. Standardized first log-differences. Datastream. Series code: NCLCS00.
Initial Jobless Claims	Number Initial Claims, Weekly, Ending Saturday, Seasonally Adjusted. Standardized first log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: ICSA.
Fed Total Assets	All Federal Reserve Banks Total Assets, Millions of Dollars, Weekly, as of Wednesday, Not Seasonally Adjusted. Standardized first log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: WALCL.
U.S. Macroeconomic Surprise Indicators	Difference between actual release and the median forecast estimate of economists surveyed by Bloomberg. Indicators: American Consumer Spending Growth Rates MoM SA (PCE CRCH:IND), Average Hourly Earnings MoM% SA (AHE MOM%:IND), Average Hourly Earnings YoY% SA (AHE YOY%:IND), Business Inventories MoM SA (MTIBCHNG:IND), Capacity Utilization % of Total Capacity (CPTICHNG:IND), Conference Board Leading Indicators MoM (LEI CHNG:IND), Construction Spending Total MoM SA (CNSTTMOM:IND), Core Producer Price Index (PPI XYOY:IND), CPI Urban Consumers Less Food & Energy YoY NSA (CPI XYOY:IND), CPI Urban Consumers MoM SA (CPI CHNG:IND), CPI Urban Consumers YoY NSA (CPI YOY:IND), Durable Goods New Orders Industries MoM SA (DGNOCHNG:IND), GDP Chained 2009 Dollars QoQ SAAR (GDP CQOQ:IND), Housing Starts/Permits (NHSPSTOT:IND), Industrial Production MoM 2007=100 SA (IP CHNG:IND), Initial Jobless Claims SA (INJCJC:IND), Markit Manufacturing PMI SA (MPMIUSMA:IND), Markit Services PMI Business Activity SA (MPMIUSSA:IND), Nonfarm Payrolls Total MoM SA (NFP TCH:IND), Personal Consumption Expenditure CPI YoY SA (PCE CYOY:IND), Personal Income MoM SA (PITLCHNG:IND), PPI Final Demand MoM SA (PCE CYOY:IND), PPI Finished Goods SA MoM% (PPI CHNG:IND), Producer Price Index - Finished Goods (PPI YOY:IND), Productivity Output Per Hour Nonfarm Business Sector QoQ SA (PRODNFR%:IND), Retail Sales (Less Auto and Gas Stations) SA MoM% Change (RSTAXAG%:IND), Trade Balance of Goods and Services SA (USTBTOT:IND), Unit Labor Costs Nonfarm Business Sector QoQ% SAAR (COSTNFR%:IND), University of Michigan Consumer Confidence Indicator (CONSSENT:IND), US Government Budget Balance FED (FDDSSD:IND).
10y TB rate	10 Year U.S. Treasury Benchmark Bond Redemption Yield, Weekly, Ending Tuesday. First absolute differences. Datastream. Series code: USBDS10Y.
Baa-Aaa spread	Difference between Moody's Seasoned Baa Corporate Bond Yield ©, Percent, Weekly, Ending Tuesday, Not Seasonally Adjusted and Moody's Seasoned Aaa Corporate Bond Yield ©, Percent, Weekly, Ending Tuesday, Not Seasonally Adjusted. First absolute difference. Federal Reserve Economic Data, St. Louis Fed. Series codes: DBAA and DAAA, respectively.
Exchange rate	Trade Weighted U.S. Dollar Index: Major Currencies, Index 27.06.2006 = 100, Weekly, Ending Tuesday. First log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: DTWEXM.
Oil price	Crude Oil Prices: West Texas Intermediate (WTI) - Cushing, Oklahoma, Dollars per Barrel, Weekly, Ending Tuesday, End of Period. First log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: DCOILWTICO.

Realized volatility	Square root of the weekly realized variance of the oil spot price, which is given by $RV_t = \sum_{j=1}^{n}(p_{t-1+\frac{j}{n}} - p_{t-1+\frac{j-1}{n}})^2$, where p_t denotes the logarithm of the oil spot price and n is the number of trading days during week t. First absolute differences. Source of the oil price see above.
S&P 500	Standard & Poor's 500 Stock Market Index, Weekly, Ending Tuesday. First log-differences (that is, the return). Yahoo Finance.
TED spread	TED Spread, Weekly, Ending Tuesday, End of Period. First absolute difference. Federal Reserve Economic Data, St. Louis Fed. Series code: TEDRATE.
VIX	CBOE Volatility Index: VIX, Weekly, Ending Tuesday, End of Period. First absolute difference. Federal Reserve Economic Data, St. Louis Fed. Series code: VIXCLS.

Definitions of Trader Groups in DCOT Reports

Below are the definitions of the four trader groups in the DCOT Reports as stated in CFTC (2018a). The fifth group of "Non-Reportables" is a residual component.

Producer/Merchant/Processor/User
An entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities.

Swap Dealer
An entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions. The swap dealer's counterparties may be speculative traders, like hedge funds, or traditional commercial clients that are managing risk arising from their dealings in the physical commodity.

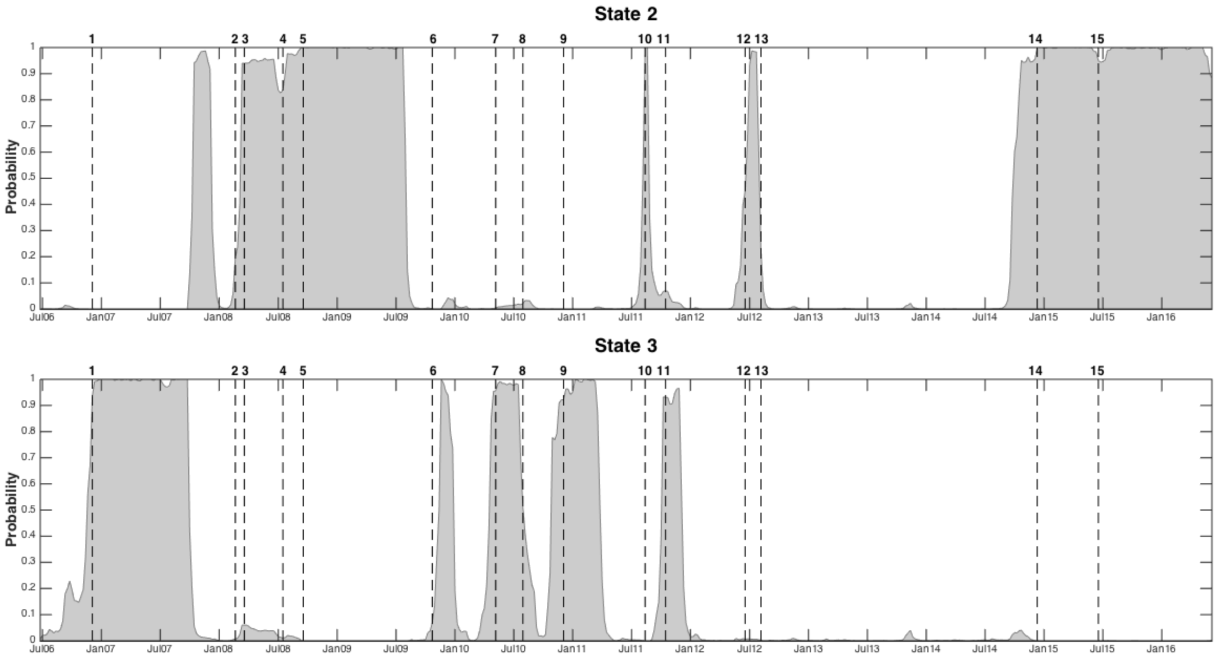
Money Manager
A registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients.

Other Reportables
Every other reportable trader that is not placed into one of the other three categories is placed into the "other reportables" category.

Non-Reportables
The remainder of total open interest in the specific futures market that is not accounted for by the other four categories of traders.

1.B Sensitivity Analysis: Additional Figure and Table

Figure 1.4: Smoothed Probabilities of the Two Volatile States in the Robustness Check



1: OPEC president expects oil output cuts; 2: Northern Rock in state ownership; 3: Bear Stearns takeover bid; 4: IndyMac Bank failure; 5: Lehman Brothers failure & AIG rescue, OPEC production cutbacks; 6: Greece's budget deficit expected to reach ~12.5% of GDP; 7: Greece bailout; 8: Dodd-Frank-Act; 9: Ireland bailout; 10: USA downgrading; 11: FED UMP announcement, ECB Covered Bond Purchase Programme; 12: Bank bailout Spain; 13: OMT London; 14: OPEC keeps production target despite oversupply; 15: OPEC Meeting

Note: Plot of the endogenously estimated smoothed probabilities of the two high volatility states, that is, the “turbulent states,” in the robustness check of the baseline model with three different states. Dashed lines correspond to selected events that are listed below the figure.

Table 1.9: Sensitivity Analysis

Alternative specification	$\rho\left(S_t(2)^{base.}, S_t(2)^{alt.}\right)$	$A(1) = \bar{A}$	$\mathcal{A}(2)$	$\Lambda(1) = \bar{\Lambda}$	$\mathit{\Lambda}(2)$
Baseline model	1.00	$\begin{pmatrix} 1 & 0 & 1.06^{***} \\ 0 & 1 & 1.52^{***} \\ -1 & -1 & 0.56 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.31 \\ 0 & 0 & -1.26^{***} \\ 0 & 0 & 0.41 \end{pmatrix}$	$\begin{pmatrix} 0.71^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 1.90^{***} \end{pmatrix}$	$\begin{pmatrix} 1.18^{***} & 0 & 0 \\ 0 & 0.45^{***} & 0 \\ 0 & 0 & 1.46 \end{pmatrix}$
Additional trader group	0.89	$\begin{pmatrix} 1 & 0 & 0 & 1.07^{***} \\ 0 & 1 & 0 & 1.28^{***} \\ 0 & 0 & 1 & 1.40^{***} \\ -1 & -1 & -1 & -0.25 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0 & -0.56^{***} \\ 0 & 0 & 0 & -1.10^{***} \\ 0 & 0 & 0 & -1.08^{***} \\ 0 & 0 & 0 & 1.45^{***} \end{pmatrix}$	$\begin{pmatrix} 0.80^{***} & 0 & 0 & 0 \\ 0 & 0.57^{***} & 0 & 0 \\ 0 & 0 & 0.79^{***} & 0 \\ 0 & 0 & 0 & 2.17^{***} \end{pmatrix}$	$\begin{pmatrix} 0.75^{***} & 0 & 0 & 0 \\ 0 & 0.26^{**} & 0 & 0 \\ 0 & 0 & 0.28^{*} & 0 \\ 0 & 0 & 0 & 2.85^{*} \end{pmatrix}$
Three states: State 2	0.71	$\begin{pmatrix} 1 & 0 & 0.85^{***} \\ 0 & 1 & 1.50^{***} \\ -1 & -1 & 0.94 \end{pmatrix}$	$\mathcal{A}(2) = \begin{pmatrix} 0 & 0 & -0.76^{***} \\ 0 & 0 & -1.37^{***} \\ 0 & 0 & 1.99 \end{pmatrix}$	$\begin{pmatrix} 0.62^{***} & 0 & 0 \\ 0 & 0.42^{***} & 0 \\ 0 & 0 & 2.43^{**} \end{pmatrix}$	$\mathit{\Lambda}(2) = \begin{pmatrix} 0.10 & 0 & 0 \\ 0 & 0.30^{***} & 0 \\ 0 & 0 & 15.67 \end{pmatrix}$
Three states: State 3	0.32		$\mathcal{A}(3) = \begin{pmatrix} 0 & 0 & 1.90^{***} \\ 0 & 0 & -1.35^{***} \\ 0 & 0 & -0.74 \end{pmatrix}$		$\mathit{\Lambda}(3) = \begin{pmatrix} 3.26^{**} & 0 & 0 \\ 0 & 0.57^{***} & 0 \\ 0 & 0 & -0.22 \end{pmatrix}$
Shorter sample period: June 12, 2007 to May 27, 2014	0.94	$\begin{pmatrix} 1 & 0 & 0.79^{***} \\ 0 & 1 & 1.61^{***} \\ -1 & -1 & 0.63 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.25 \\ 0 & 0 & -1.31^{***} \\ 0 & 0 & -0.11 \end{pmatrix}$	$\begin{pmatrix} 0.56^{***} & 0 & 0 \\ 0 & 0.41^{***} & 0 \\ 0 & 0 & 2.15^{**} \end{pmatrix}$	$\begin{pmatrix} 2.06^{***} & 0 & 0 \\ 0 & 0.32^{***} & 0 \\ 0 & 0 & 0.15 \end{pmatrix}$
Switching intercept	0.99	$\begin{pmatrix} 1 & 0 & 1.06^{***} \\ 0 & 1 & 1.51^{***} \\ -1 & -1 & 0.50 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.33 \\ 0 & 0 & -1.27^{***} \\ 0 & 0 & 0.50 \end{pmatrix}$	$\begin{pmatrix} 0.71^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 1.85^{***} \end{pmatrix}$	$\begin{pmatrix} 1.12^{***} & 0 & 0 \\ 0 & 0.42^{***} & 0 \\ 0 & 0 & 1.63 \end{pmatrix}$
Additional exogenous variables	0.88	$\begin{pmatrix} 1 & 0 & 1.00^{***} \\ 0 & 1 & 1.33^{***} \\ -1 & -1 & 1.71^{*} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.03 \\ 0 & 0 & -1.09^{***} \\ 0 & 0 & -0.57 \end{pmatrix}$	$\begin{pmatrix} 0.61^{***} & 0 & 0 \\ 0 & 0.47^{***} & 0 \\ 0 & 0 & 2.90^{**} \end{pmatrix}$	$\begin{pmatrix} 1.67^{***} & 0 & 0 \\ 0 & 0.55^{***} & 0 \\ 0 & 0 & 0.09 \end{pmatrix}$
No exogenous variables	0.89	$\begin{pmatrix} 1 & 0 & 0.99^{***} \\ 0 & 1 & 1.29^{***} \\ -1 & -1 & 0.62^{*} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.35 \\ 0 & 0 & -1.02^{***} \\ 0 & 0 & -0.50 \end{pmatrix}$	$\begin{pmatrix} 0.80^{***} & 0 & 0 \\ 0 & 0.62^{***} & 0 \\ 0 & 0 & 2.05^{***} \end{pmatrix}$	$\begin{pmatrix} 1.17^{***} & 0 & 0 \\ 0 & 0.44^{***} & 0 \\ 0 & 0 & 2.67 \end{pmatrix}$
Four lags of the endogenous variables	0.94	$\begin{pmatrix} 1 & 0 & 0.76^{***} \\ 0 & 1 & 1.48^{***} \\ -1 & -1 & 0.94 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.07 \\ 0 & 0 & -1.23^{***} \\ 0 & 0 & 0.03 \end{pmatrix}$	$\begin{pmatrix} 0.51^{***} & 0 & 0 \\ 0 & 0.40^{***} & 0 \\ 0 & 0 & 2.34^{**} \end{pmatrix}$	$\begin{pmatrix} 1.43^{***} & 0 & 0 \\ 0 & 0.48^{***} & 0 \\ 0 & 0 & 1.08 \end{pmatrix}$
Predetermined exogenous variables	0.89	$\begin{pmatrix} 1 & 0 & 0.65^{***} \\ 0 & 1 & 1.25^{***} \\ -1 & -1 & 2.15 \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & 0.31 \\ 0 & 0 & -0.97^{***} \\ 0 & 0 & -1.35 \end{pmatrix}$	$\begin{pmatrix} 0.46^{***} & 0 & 0 \\ 0 & 0.36^{***} & 0 \\ 0 & 0 & 4.53 \end{pmatrix}$	$\begin{pmatrix} 1.76^{***} & 0 & 0 \\ 0 & 0.59^{***} & 0 \\ 0 & 0 & -1.83 \end{pmatrix}$
Futures basis instead of futures price	0.26	$\begin{pmatrix} 1 & 0 & 1.28^{***} \\ 0 & 1 & 1.44^{***} \\ -1 & -1 & 11.70^{***} \end{pmatrix}$	$\begin{pmatrix} 0 & 0 & -0.98^{**} \\ 0 & 0 & -1.11^{***} \\ 0 & 0 & -11.14^{***} \end{pmatrix}$	$\begin{pmatrix} 0.93^{***} & 0 & 0 \\ 0 & 0.84^{***} & 0 \\ 0 & 0 & 8.70^{*} \end{pmatrix}$	$\begin{pmatrix} 1.48^{*} & 0 & 0 \\ 0 & 0.51 & 0 \\ 0 & 0 & -5.87 \end{pmatrix}$

Note: The table reports the main results of the following robustness tests: a model including a third trader group (the DCOT group "Others"), a model with three states, a model encompassing a shorter sample period, a model featuring a switching intercept, a model with additional exogenous variables and one without any exogenous variables, a model with four lags of the endogenous variables, a model which allows for predetermined exogenous variables, and a model in which the futures basis is used instead of the futures price. The first row contains the results for the baseline model. The second column states the correlation between the turbulent state of the baseline model and the alternative model (in case of the three-state model among the turbulent state of the baseline model and both volatile states of the alternative model). The remaining columns display the matrix A of instantaneous relations among the endogenous variables and its switch $\mathcal{A}(2)$ to the turbulent state ($\mathcal{A}(2)$ and $\mathcal{A}(3)$ in case of the three-state model), as well as the variances of the identified demand shocks $\Lambda(1)$ and their switch $\mathit{\Lambda}(2)$ to the turbulent state ($\mathit{\Lambda}(2)$ and $\mathit{\Lambda}(3)$ in case of the three-state model). *, **, *** indicate significance at the 10%, 5%, and 1% level, respectively. The full set of results is available upon request.

CHAPTER 2

An Empirical Characterization of Commodity Futures Trading[1]

2.1 Introduction

Since the formation of financial markets researchers, regulators and financial analysts have studied the trading behavior of market participants and tried to understand the implications of different trading strategies for market outcomes. Broadly speaking, traders can follow two diametrically opposed main strategies: momentum or contrarian trading (Conrad and Kaul, 1998). The former hinges on price continuations and calls for buying assets that have outperformed in the recent past. The latter does the exact opposite, investing in assets that have underperformed and selling those that have done well. Heterogeneity in the trading behavior of different market participants gives rise to different motives for demand for assets and risk sharing in markets (Kaniel et al., 2008, Menkhoff et al., 2016). By selling assets when prices rise, contrarian traders provide liquidity to momentum-trading market participants that demand immediacy in return for price concessions. They can thus be interpreted as liquidity-providing market makers who stabilize prices and reduce volatility (Grossman and Miller, 1988, Campbell et al., 1993, Weill, 2007, Nagel, 2012). Momentum traders, on the other hand, consume liquidity in the market and increase price volatility. Further, momentum trading has been shown to suffer from infrequent but costly periods of negative returns (Barroso and Santa-Clara, 2015, Daniel and Moskowitz, 2016) and is positively related to liquidity risk in several asset markets (Asness et al., 2013).

Gaining insights into the trading behavior of different market participants is crucial for understanding the functioning of asset markets, their observed price dynamics and liquidity patterns, as well as regarding their design. In this paper, we propose a simple approach for structurally estimating the trading pattern of different market participants in a given asset market. The multivariate simultaneous equation system is based on stylized theoretical deliberations following Cheng et al. (2015) and describes the trading behavior of different trader groups in terms of simple net long demand curves depending on the contemporaneous asset price and a group-specific demand shock. Hence, the model captures two main trading motives of traders: liquidity provision following endogenous price movements and trading for own purposes based on exogenous private signals. In contrast to commonly employed single equation models, our framework makes use of methodologies that are widely applied mainly in the macroeconomic literature and that have been developed to address problems of simultaneity. It can enhance single equation models

[1] This chapter is based on joint work with Malte Rieth.

where identification is typically achieved via lead-lag relationships along two dimensions. First, it allows modeling contemporaneous relationships between prices and positions. This is particularly relevant given the development of financial markets with electronic and algorithmic trading where market participants respond to price developments in essentially continuous time. Second, the approach facilitates a decomposition of observed price dynamics into the contributions of different trader groups and their trading behavior.

As an empirical application we study commodity futures markets, using two different publicly available datasets from the U.S. Commodity Futures Trading Commission (CFTC) which differ in their classification of traders. Commodity futures markets have received increasing attention recently by investors, policy makers and academics alike due the observed increase in the presence of financial traders and in open interest, a phenomenon known as the "financialization of commodity markets" (Domanski and Heath, 2007). This development has questioned long-standing traditional views like the theory of normal backwardation (Keynes, 1930, Hicks, 1939) and its generalization through the hedging-pressure theory (Hirshleifer, 1990) on the functioning of commodity futures markets (Cheng and Xiong, 2014, Basak and Pavlova, 2016, Chari and Christiano, 2017). The growing evidence points towards financial traders pursuing own investment strategies and trading objectives which are independent of meeting producers' hedging demands (Moskowitz et al., 2012, Rouwenhorst and Tang, 2012, Kang et al., 2017). This goes hand in hand with mutual risk sharing among the various trader groups in commodity markets (Cheng et al., 2015, Chari and Christiano, 2017).

We relate to the works of Kaniel et al. (2008) on investor trading in the stock market and Menkhoff et al. (2016) who study the foreign exchange market, but focus our analysis on commodity futures markets. The paper contributes to a better understanding on how different market participants affect price dynamics and liquidity in the market through their specific trading behavior. The multivariate empirical model, which is identified through theory and allows for quantifying price and liquidity effects of different trading strategies, distinguishes our work from Rouwenhorst and Tang (2012) and Kang et al. (2017). They both infer trading patterns based on the direction of the predictability of short-term returns following position changes of traders. From a policy perspective, we can compare the different trader classifications across two CFTC reports, namely the Disaggregated Commitments of Traders (DCOT) report and the Supplemental Commitments of Traders (SCOT) report.

In sum, our results show that producers are contrarian traders who mainly provide liquidity to financial traders. Swap dealers who are mostly large banks trading on behalf of their clients or on their own behalf are on average contrarian traders as well, but experience themselves periods in which they restrict liquidity provision, in particular during times associated with general financial market turmoil (Cheng et al., 2015, Bierbaumer et al., 2018). Qualitatively, this also holds for other, not further classified financial traders, the specific group of commodity index traders (CITs), and small traders that are not obliged to report their positions in the market. In contrast, non-commercial traders and, more specifically, money managers like commodity trading advisors (CTAs) or commodity pool operators (CPOs) follow momentum strategies and consume liquidity. However, the associated price effects and the demand for liquidity is comparatively small. Our results are thus in line with Rouwenhorst and Tang (2012) who find that non-commercials are momentum traders and commercials are on average contrarian traders as well as with Chari and Christiano (2017) who argue that all market participants in commodity futures markets insure each other mutually. Our findings differ a bit from those of Kang et al. (2017) who find that producers are the only trader group providing liquidity, while all other traders are short-term consumers of liquidity, especially money managers. We get similar results for producers and money managers, but in terms of swap dealers and other reportables our estimates point towards them being contrarian traders.

The chapter proceeds as follows. The next section first discusses the literature on trading behavior in asset markets in general and commodity futures markets in particular, and then presents our simple theoretical framework. Section 2.3 describes the data and outlines the empirical methodology. Section 2.4 contains the main results as well as some robustness checks on the specification of the three core models. The last section concludes.

2.2 Literature and Theoretical Background

We start this section by briefly discussing related works and describe how our approach contributes to the literature. We then present a simple theoretical model that describes the market behavior and trading strategies of different trader groups in asset markets. Since our empirical application studies commodity futures markets, we also relate to the trader groups present in these markets when explaining the model, although the model can be adapted to any asset market with at least three trader groups.

Broadly speaking, market participants can follow two diametrically opposed main trading strategies, namely the momentum or the contrarian strategy (Conrad and Kaul, 1998). The momentum strategy hinges on price continuations and calls for buying assets that have outperformed in the recent past (past winners) and selling those that underperformed (past losers).[2] In contrast, traders pursuing a contrarian strategy invest in assets that have underperformed and withdraw those that have done well. Heterogeneity in the trading behavior of different market participants gives rise to different motives for demand for assets and risk sharing in markets (Kaniel et al., 2008, Menkhoff et al., 2016). By selling assets when prices rise, contrarian traders provide liquidity to momentum-trading institutions that demand immediacy, thereby receiving price concessions, stabilizing prices, and reducing volatility. They can thus be interpreted as liquidity-providing market makers, even though they might not officially designated to take on this role (Grossman and Miller, 1988, Campbell et al., 1993, Weill, 2007, Nagel, 2012). Momentum traders, on the other hand, consume liquidity in the market, raise price volatility, and have

[2] A special case of a momentum strategy is pure trend-following. While the former features both a cross-sectional and a time-series component, the latter relies solely on the time-series dimension.

been shown to suffer from infrequent but costly periods of negative returns (Barroso and Santa-Clara, 2015, Daniel and Moskowitz, 2016). Moreover, momentum trading is positively related to liquidity risk in several asset markets (Asness et al., 2013).

Gaining insights into the trading behavior of different market participants is crucial for understanding the functioning of asset markets, their observed price dynamics and liquidity patterns, as well as regarding their design. Kaniel et al. (2008) study the role of individual investor trading for a large cross-section of NYSE stocks and find that individuals tend to follow contrarian trading strategies, thereby providing liquidity to meet institutional investors' demand for immediacy. Likewise, Menkhoff et al. (2016) analyze the foreign exchange market and show that different customer groups are heterogenous in terms of trading behavior as well as their exposure to risk and hedge factors, and that they engage in risk sharing with each other through the intermediation of a large dealer. Recently, there has been growing interest in commodity futures markets following an increasing presence of financial traders in these markets that has led to institutional changes, a phenomenon known as "financialization of commodity markets" (Domanski and Heath, 2007). This development has questioned long-standing traditional views on the functioning of commodity futures markets (Cheng and Xiong, 2014, Basak and Pavlova, 2016, Chari and Christiano, 2017).[3]

Regarding the trading behavior of participants in commodity futures markets[4], Moskowitz et al. (2012) provide evidence that speculators trade in the same direction as return shocks while hedgers take the opposite of these trades, which indicates that speculators on average profit from time series momentum at the cost of hedgers. Brunetti and Reiffen (2014) show that commodity index traders (CITs), who have become major suppliers of price risk insurance sought by hedgers over the two recent decades, reduce hedging costs in commodity futures markets. Rouwenhorst and Tang (2012) document that non-commercials are momentum traders, while commercials are on average contrarian traders, and that the positions of index traders and swap dealers show very little sensitivity to futures returns at short horizons. Similarly, Balta and Kosowski (2013) point out that commodity trading advisors (CTAs) follow time-series momentum strategies in commodity futures markets. Kang et al. (2017) find that in the short term speculative traders are actually driving position changes in commodity futures markets and hence are consuming liquidity. Moreover, they demonstrate that the expected excess return to a commodity futures contract embeds two opposing premiums; the traditional one paid by hedgers to speculative traders for obtaining price insurance plus one paid by speculative traders to hedgers for satisfying

[3] Traditional views such as the theory of normal backwardation (Keynes, 1930, Hicks, 1939) and its generalization through the hedging-pressure theory (Hirshleifer, 1990) are based on the notion that insurance-seeking hedgers consume the liquidity provided by speculative traders that require a risk premium in exchange. That is, financial traders facilitate risk sharing for hedgers by providing insurance for price fluctuations in the future.

[4] For papers studying the performance of different investment strategies in commodity futures markets see inter alia Wang and Yu (2004), Erb and Harvey (2006), Miffre and Rallis (2007), Shen et al. (2007), Marshall et al. (2008), Szakmary et al. (2010), Narayan et al. (2014), and Neuhierl and Thompson (2016), for contributions investigating whether speculative trading has been a driver of the observed boom in commodity prices see inter alia Stoll and Whaley (2011), Henderson et al. (2015), Singleton (2014), and Hamilton and Wu (2015).

their short-term demand for liquidity. Likewise, Chari and Christiano (2017) argue that all market participants in commodity futures markets insure each other mutually, while Cheng et al. (2015) report a risk transfer from financial traders to hedgers during times when the risk absorption capacity of the former, as measured by the VIX, is low.

We relate to the works of Kaniel et al. (2008) on investor trading in the stock market and Menkhoff et al. (2016) who study the foreign exchange market. While their empirical strategy is different from ours, we are interested in similar questions with respect to commodity futures markets. In particular, we aim to characterize the trading of different market participants in commodity futures markets and the associated effects on futures prices and market liquidity. We propose a multivariate simultaneous equation system that enables us to analyze the trading behavior of several trader groups contemporaneously. The framework allows us to quantify the price impacts and liquidity effects of the different trading strategies employed by market participants, thereby gaining an insight who is driving prices to what extent. Since we can model the whole market, we can include all trader groups as classified by the CFTC and do not need to restrict the analysis to the large, heterogenous groups of commercials and non-commercials as common in other studies. From a policy perspective, we can compare the different trader classifications across two CFTC reports, namely the Disaggregated Commitments of Traders (DCOT) report and the Supplemental Commitments of Traders (SCOT) report. This comprehensive empirical approach distinguishes our work from Rouwenhorst and Tang (2012) and Kang et al. (2017), who both infer trading patterns based on the direction of the predictability of short-term returns following position changes of traders.

We start by formulating a stylized model of a commodity futures market to develop an idea how different market participants trade with each other. The model setup follows Cheng et al. (2015) and describes the trading behavior of typical trader groups present in commodity futures markets, who are all assumed to be atomistic price takers. For illustration purposes, we outline the model for the case of data from the DCOT report which comprises five different trader groups. These are producers/processors/merchants (henceforth producers, p), swap dealers (s), money managers (m), other reportables (henceforth others, o), and a residual group of non-reportables (n). For each of these trader groups we formulate a net long demand curve as follows:

$$\Delta y^i = -a^i \Delta P + b^i \ \nu^i,$$

where Δy^i denotes the change in the net long commodity futures position of trader group $i = p, s, m, o, n$ and ΔP is the change in the commodity futures price. The coefficients a^i determine the slope of the respective demand curve and thus indicate whether one trader group on average acts as a momentum trader ($a^i < 0$) or as a contrarian trader ($a^i > 0$) in a given commodity market.[5] Further note that these coefficients measure the price elasticity of demand of each group, implying that we are also able to quantify the endogenous reaction of traders in response

[5] In estimating the model we obtain the coefficients a^i, but when interpreting the results we need to consider $-a^i$ as stated in the equation system.

to price changes caused by trading incentives of other traders. For instance, if $a^s > a^o > 0$ then we would conclude first that both trader groups, swap dealers and others, are contrarian traders and second that swap dealers have a greater capacity or willingness to absorb a larger part of the desired demand shifts of other trader groups than others for a given futures price change. Technically, swap dealers would be more price-elastic than others, implying that their demand curve is relatively flatter. In terms of liquidity, we can infer that contrarian traders are providing liquidity during periods of rising futures prices, while momentum traders are consuming this liquidity, and vice versa. Illiquidity might arise if there are limits to arbitrage which deter risk-averse arbitrageurs from taking the counter-side. Shleifer and Summers (1990) and Shleifer and Vishny (1997), for example, show that large position changes can influence prices through an effect on the order book if the instantaneous supply of counterparty orders is low.

Each demand curve further features a random shock ν^i which causes the respective trader group to adjust its net long position following their own purposes based on exogenous, private signals. The b^i's measure the impact of these shocks and are allowed to differ across groups, that is, they are group-specific. One can interpret these coefficients as the exposure of each trader group to its idiosyncratic shocks. For example, if we think of ν^s as a shock hitting the balance sheet of swap dealers, then a larger b^s suggests a greater exposure to this shock. Thus, in sum, our stylized demand model captures two main trading motives of traders in financialized commodity futures markets: liquidity provision to other traders and trading for own purposes. The usual market clearing condition $\Delta y^p + \Delta y^s + \Delta y^m + \Delta y^o + \Delta y^n = 0$ closes the model and ensures that the price is jointly determined by all trader groups in equilibrium. Making use of it and writing the system in matrix notation yields

$$\begin{pmatrix} 1 & 0 & 0 & 0 & a^p \\ 0 & 1 & 0 & 0 & a^s \\ 0 & 0 & 1 & 0 & a^m \\ 0 & 0 & 0 & 1 & a^o \\ -1 & -1 & -1 & -1 & a^n \end{pmatrix} \begin{pmatrix} \Delta y^p \\ \Delta y^s \\ \Delta y^m \\ \Delta y^o \\ \Delta P \end{pmatrix} = \begin{pmatrix} b^p \\ b^s \\ b^m \\ b^o \\ b^n \end{pmatrix} \tag{2.1}$$

This expression is the basis for the identification of our structural empirical model. It illustrates our main identifying restrictions which are reflected in the zero elements on the LHS of (2.1). We assume that no trader group responds directly to the position change of any other group. This assumption is consistent with the publication lag of the CFTC data that we use and the markets to which they refer. The positions correspond to each Tuesday end-of-day at the electronic trading platform where the specific commodity is traded (see Appendix 2.A for details). At these platforms aggregated orders of other investors are not observable and the CFTC reports are released only the following Friday, implying that traders cannot contemporaneously observe and thus directly respond to aggregated position changes of other groups. They do so, of course, indirectly through prices. The model using data from the SCOT report is equivalent, but is only composed of four trader groups, which are commercials (c), non-commercials (nc), commodity index traders (cit) and the residual group non-reportables (n). Finally, unlike Cheng et al. (2015), our framework does not contain a common shock which simultaneously affects all trader groups (potentially to differing degrees). Instead, we deal which such shocks by including two exogenous control variables in the baseline empirical model and by adding several further controls in a robustness check.

2.3 Data and Estimation

In this section we first describe the data employed in the analysis, focusing on the position data from the two CFTC reports. Then we outline the empirical model and its estimation.

2.3.1 Data

We use position data of two main reports of the U.S. Commodity Futures Trading Commission (CFTC), namely the Disaggregated Commitments of Traders (DCOT) report and the Supplemental Commitments of Traders (SCOT) report (see Irwin and Sanders (2012) for a detailed description of CFTC datasets). The data cover the long and short positions of traders in commodity futures markets and are weekly. In terms of commodity futures prices, we employ the continuous nearby (next-to-maturity) futures settlement price of each commodity. Our sample runs from June 13, 2006 to October 24, 2017, containing 594 observations.

There are two main differences between the DCOT and SCOT data. First, the SCOT data comprises trading positions in the futures market only for a range of agricultural commodities of which we use eleven for our analysis.[6] Commodity coverage of the DCOT data is broader, including in addition to agricultural commodities also energy resources and precious metals. This enables us to employ all commodities that are part of the S&P GSCI but gold in our empirical application.[7]

Second, the DCOT data classifies market participants into five trader groups (producers/processors/merchants, swap dealers, money managers, other reportables, and non-reportables), while in the SCOT data four trader groups (commercials, non-commercials, commodity index traders, and non-reportables) are distinguished.[8] In detail, regarding DCOT data one typically thinks of the first group of producers who are actively engaged in the physical markets and use futures to hedge against spot price risks. The second group of swap dealers consists mainly of large banks (Heumesser and Staritz, 2013) that either trade on behalf of clients without direct access to the futures market or on their own behalf. As the name suggest, they deal primarily in swaps and hedge those transactions in the futures market. Money managers include commodity trading

[6] These are wheat SRW, wheat HRW, corn, soybeans, cotton, lean hogs, live cattle, feeder cattle, cocoa, sugar, and coffee.

[7] These are the eleven agricultural commodities also used in the SCOT analysis as well as WTI crude oil, heating oil, RBOB gasoline, natural gas, copper, and silver. We exclude gold due to its special feature as a safe-haven asset.

[8] Definitions of all trader groups in the two reports are given in Appendix 2.A.

advisors (CTAs), along with commodity pool operators (CPOs) and other unregistered funds, all of which usually trade on behalf of clients. The category other reportables encompasses all remaining reportable traders that do not fit in any of the three above mentioned categories, for instance, large individual traders. As such, trading motives and business models of this group are likely to be quite heterogenous. Finally, non-reportables is a residual component of small traders who are not obliged to report to the CFTC and is made up of the remainder of total open interest in a specific market that is not accounted for by any of the other four categories. The SCOT report extracts commodity index traders (CITs) who seek index exposure to commodities from commercials and non-commercials, where CITs include both non-commercial institutional investment funds and commercial swap dealers that exhibit indexing trading patterns (Irwin and Sanders, 2012, Cheng et al., 2015). In sum, both datasets have their merits and shortcomings and which one to use hinges on the specific research question. We perform our empirical analyses with position data from both reports, which enables us to compare the trader classifications between the two reports.

One caveat of the CFTC data are potential misclassifications of traders and hence reporting errors. First, financial traders have incentives to be classified as hedgers since this entitles them to preferential treatments. Hedgers are exempted from position limits and face lower margins requirements, translating into less capital needed for maintaining open positions. Second, the data refer to total end-of-day positions of traders, meaning that positions are aggregated across trades due to different business reasons. This aggregation complicates an interpretation of position changes. Third, the CTFC itself changes the classification of traders from time to time, for example following alterations in the way traders participate in the futures market. Overall, misclassifications cannot be fully excluded.

For our main empirical analysis, we construct three weighted aggregate indexes: a DCOT aggregate including 17 agricultural, energy, and metal commodities, a DCOT aggregate comprising eleven agricultural commodities only, and a SCOT aggregate of the same eleven agricultural commodities. The weights of the individual commodities in each index are based on the commodities' yearly varying weights in the S&P GSCI (see Table 2.7 in Appendix 2.A). In addition, we also estimate the model for each single commodity futures market separately, that is, for 17 commodities using DCOT position data and eleven commodities using SCOT position data. The position variables enter the model as the standardized first absolute difference of the net long position of each trader group and the futures price in standardized first log-differences. Aggregation of positions for the indexes is accomplished by first dividing by the average total open interest in 2006 in each specific commodity futures market to account for different contract sizes, followed by summing up the markets by applying the respective weights. Due to different price levels, the aggregate futures price is obtained by first taking the log-difference for each commodity futures price and then by aggregating them according to the S&P GSCI weights.

Finally, we augment the model with two contemporaneous exogenous variables to control for common factors that potentially affect positions of all trader groups simultaneously. We add the number of initial jobless claims to capture the state of the real economy and the balance sheet of the Fed to account for nominal developments. Both variables are available at the weekly frequency. In Section 2.4.4 we show that the results are largely insensitive to including the surprise component in news releases of 30 U.S. macroeconomic indicators as additional exogenous variables. Appendix 2.A contains a complete description of the data used in the analysis.

2.3.2 Empirical Model

The empirical model follows directly from the theoretical model presented in the previous section and is in its essence a multivariate simultaneous equation system corresponding to a commodity futures market:

$$y_t = c + \Gamma_1 y_{t-1} + \cdots + \Gamma_p y_{t-p} + \Psi_1 x_{t-1} + \cdots + \Psi_n x_{t-n} + u_t, \tag{2.2}$$

where y_t is the vector of endogenous variables. In our specifications featuring DCOT position data there are five endogenous variables, that is, $y_t = [\Delta y_t^p, \Delta y_t^s, \Delta y_t^m, \Delta y_t^o, \Delta P_t]'$, while in the case of SCOT position data we have $y_t = [\Delta y_t^c, \Delta y_t^{nc}, \Delta y_t^{cit}, \Delta P_t]'$. Further, x_t is a vector of W exogenous variables, Γ_i and Ψ_j are parameter matrices with $i = 1, \ldots, p$, and $j = 1, \ldots, n$, and c is a vector of constants. In our case, we set $p = 1$ and $n = 1$ based on information criteria and perform a robustness check with $p = n = 4$. Finally, u_t is a vector of reduced form error terms with $\mathbb{E}[u_t] = 0$ and $\mathbb{E}[u_t u_t'] = \Sigma_u$. For estimation purposes, we assume that u_t is normally and independently distributed, $u_t \sim \text{NID}(0, \Sigma_u)$.

Based on the theoretical model in (2.1), the structural empirical model for the case of DCOT data is given by

$$\underbrace{\begin{bmatrix} 1 & 0 & 0 & 0 & a^p \\ 0 & 1 & 0 & 0 & a^s \\ 0 & 0 & 1 & 0 & a^m \\ 0 & 0 & 0 & 1 & a^o \\ -1 & -1 & -1 & -1 & a^n \end{bmatrix}}_{\equiv A} \underbrace{\begin{bmatrix} u_t^p \\ u_t^s \\ u_t^m \\ u_t^o \\ u_t^n \end{bmatrix}}_{=u_t} = \underbrace{\begin{bmatrix} b^p & 0 & 0 & 0 & 0 \\ 0 & b^s & 0 & 0 & 0 \\ 0 & 0 & b^m & 0 & 0 \\ 0 & 0 & 0 & b^o & 0 \\ 0 & 0 & 0 & 0 & b^n \end{bmatrix}}_{\equiv B} \begin{bmatrix} \epsilon_t^p \\ \epsilon_t^s \\ \epsilon_t^m \\ \epsilon_t^o \\ \epsilon_t^n \end{bmatrix},$$

where $\epsilon_t = [\epsilon_t^p, \epsilon_t^s, \epsilon_t^m, \epsilon_t^o, \epsilon_t^n]'$ is a vector of structural demand shocks, and where we have neglected constants, lags and exogenous variables for illustration. This leads to the following relationship between the reduced form errors and the structural shocks: $Au_t = B\epsilon_t$, where A is a matrix of instantaneous relations among the endogenous variables, B is a matrix of potential relations among the structural innovations, and $\mathbb{E}[\epsilon_t \epsilon_t'] = I_K$.

Regarding identification of the model, note that we obtain from $\Sigma_u = A^{-1}BB'A^{-1\prime}$ in total $K * (K+1)/2$ unique equations that are sufficient to pin down the structural moments. The specific structure of the A-matrix directly follows from the theoretical model and is motivated by the observation that traders view trades of other market participants only with a considerable lag.

Despite these zero restrictions, all variables in the model are allowed to react contemporaneously to any structural demand shock since the linear function $A^{-1}B$ that relates the reduced form residuals u_t to the structural demand shocks ϵ_t, that is $u_t = A^{-1}B\epsilon_t$, has non-zero elements. This is a central feature of the model and a main building block of the empirical plausibility of our identifying assumptions as financial market variables are likely to respond to each other in nearly continuous time.

2.4 Results

This section presents our main results. We first show our estimates regarding the trading behavior of the different trader groups for the three aggregate core models. We then study the price effects associated with these trading strategies and utilize the model to infer the contribution of them to the futures price. Finally, we perform a scenario analysis in which we distinguish the traders' endogenous reaction to prices from trading following exogenous trader-specific signals over the whole sample period.

2.4.1 Contrarian Traders versus Trend-Followers

We begin by presenting results on the estimated parameters of the A matrix of instantaneous relations between the endogenous variables. Since the matrix corresponds to the one in the theoretical framework we can interpret these coefficients as the slope parameters of the net long demand curves of the different trader groups, or put differently, as their price elasticity. Remember that we obtain from the estimations the coefficients a^i, but need to consider $-a^i$ when interpreting the results. Hence, negative values of a point to trend-following strategies, whereas a positive a-coefficient signals that the respective trader group follows a contrarian trading strategy. To evaluate the statistical significance of the parameters, we compute standard errors derived from the Hessian matrix.

Table 2.1 displays the estimated coefficients for the two aggregate DCOT models featuring 17 and eleven commodities, respectively. The values in the parentheses show the standard errors and indicate that all coefficients are highly statistically significant. Producers, swap dealers, others and the residual group of non-reportables exhibit a positive a-coefficient, implying that for these trader groups the slope coefficient is negative. Hence, they are contrarian traders who decrease their net long positions in response to increases in the futures return and provide liquidity to other market participants. Interpreting the coefficients in terms of price elasticities, producers are the group most willing to take counter-positions, followed by others and swap dealers. In contrast, the slope coefficient of the demand curve of money managers is negative, albeit with a comparatively smaller absolute value. This means that money managers seem to follow a momentum trading strategy and increase their net long position when futures prices increase. This pattern generally holds for the agricultural DCOT aggregate, although the magnitude changes for all groups but producers. Non-reportables now have the flattest demand curve, followed by producers and

Table 2.1: Net Long Demand Curve Slope Coefficients - DCOT Aggregates

	a^p	a^s	a^m	a^o	a^n
DCOT Aggregate 17 Commodities	0.85	0.56	-0.16	0.75	0.28
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)
DCOT Aggregate 11 Commodities	0.87	0.27	-0.26	0.54	0.91
	(0.03)	(0.05)	(0.04)	(0.06)	(0.08)

Note: The table shows the estimated net long demand curve slope estimates for the different trader groups in the two DCOT aggregate models of 17 commodities (including agricultural and energy commodities as well as precious metals) and eleven agricultural commodities, respectively. Standard errors are given in parentheses.

others. Hence, in agricultural markets small non-reportable traders seem to be important in providing liquidity. The coefficient for swap dealers cuts in half, implying that in agricultural markets swap dealers seem to be less willing to take counter-positions when compared to futures markets for energy and metal commodities, while money managers are found to have a larger negative value.[9]

The results of the DCOT aggregate comprising eleven agricultural commodities can be directly compared to the SCOT aggregate which contains the identical commodities (Table 2.2). Again all coefficients are highly significant. Regarding the group of commercials we find a positive coefficient that matches quantitatively almost the one from producers in the DCOT aggregate. Non-commercials exhibit a negative coefficient, mirroring qualitatively and also quantitatively money managers from the DCOT report. CITs exhibit a positive coefficient and follow a contrarian trading strategy in agricultural commodities futures market and are thus on average providing liquidity. The same applies to the residual group of non-reportables, albeit with a smaller absolute value of the coefficient when compared to the DCOT aggregate.

Table 2.2: Net Long Demand Curve Slope Coefficients - SCOT Aggregate

	a^c	a^{nc}	a^{cit}	a^n
SCOT Aggregate 11 Commodities	0.95	-0.20	0.59	0.52
	(0.04)	(0.04)	(0.09)	(0.04)

Note: The table shows the estimated net long demand curve slope estimates for the different trader groups in the SCOT aggregate model of eleven agricultural commodities. Standard errors are given in parentheses.

Taken together, we derive the following conclusions from our estimates. First, most trader groups exhibit a contrarian trading behavior and are thus willing to absorb trades from other market participants. They provide liquidity to their counterparties and stabilize prices. Swap dealers and others seem to be more price elastic in futures markets for energy resources and precious metals when compared to agricultural commodities, whereas for non-reportables the opposite is true. The exception are money managers who follow a momentum strategy, thereby

9 We do not report the estimated coefficients of the B matrix which are not in the focus of the analysis as they merely measure the impact of the group-specific demand shifts on the own net long position. These results are available upon request.

consuming liquidity and raising price volatility. Comparing the DCOT trader classifications with the SCOT one, we see that commercials match producers, while non-commercials in the SCOT data resemble money managers in the DCOT data. CITs are contrarian traders and are willing to absorb trades from other market participants, providing liquidity and risk insurance to them. Our results thus confirm previous findings by Rouwenhorst and Tang (2012) who report that non-commercials are momentum traders and commercials are contrarian traders. Likewise, they are in line with Balta and Kosowski (2013) who demonstrate that commodity trading advisors (CTAs) which are part of the trader group of money managers follow time-series momentum strategies. Regarding CITs our results are in accordance with Brunetti and Reiffen (2014) according to which CITs have become major suppliers of price risk insurance for hedgers. Our results are a bit different from those of Kang et al. (2017) who find that producers are the only trader group providing liquidity, while all other traders are short-term consumers of liquidity. However, we show below that one needs to distinguish traders' motives for trading, namely whether they are trading in reaction to endogenous price variations or following exogenous private signals. Results presented in this section mirror the former, while demand shifts due to exogenous information are associated with trader groups consuming liquidity regardless whether they are on average contrarian or momentum traders. In sum, our results provide evidence that trading patterns in commodity futures market are more complex and point towards the mutual insurance view of Chari and Christiano (2017).

This general pattern mostly holds for all individual commodity futures markets as well (Table 2.8 in Appendix 2.B). Most parameters are statistically significant and producers, swap dealers, and others (DCOT) as well as commercials and CITs (SCOT) exhibit contrarian trading in all individual markets. The same is true for non-reportables with the futures market for silver being an exception. The trading behavior of money managers and non-commercials, respectively, seems to be more diverse. The estimated demand curve slope parameter of money managers is not significant in the markets for lean hogs, live cattle, feeder cattle, and RBOB gasoline, while we obtain a statistically significantly positive estimate in case of natural gas. Likewise, we obtain no significant parameter estimate for non-commercials in the SCOT specification for wheat HRW and cotton, and a statistically positive estimate for lean hogs, live cattle (both at the 1% level), and feeder cattle (at the 10% level).

2.4.2 Price Effects of Endogenous Trading Behavior

An advantageous feature of our empirical model is its ability to quantify the price effects that are associated with the trading behavior of the different trader groups. For this purpose, note that we can compute the total effect of individual structural demand shifts on the futures return and the traders' net long position by $C = A^{-1}B$, with A^{-1} reflecting the impact that can be traced back directly to the trading behavior of the trader groups. Further, we are just interested in the effect on the futures return, which is given by the last row of matrix A^{-1} and is naturally the same for all trader groups since every unit shift in the net long demand curve has the same effect. Technically this coefficient is given by $1/\tilde{a}$ with $\tilde{a}$ being the sum of the trader groups' individual demand curve slope coefficients. The second column labelled "baseline" in Table 2.3 shows the impact on the futures return for the two DCOT aggregate models with the associated standard errors in parentheses.[10] As expected, we find an almost exact and highly significant return effect in response to a demand shift of any trader group that is only based on A^{-1} in the two models.

Table 2.3: Price Effects of Trading Strategies - DCOT Aggregates

	baseline	p	s	m	o	n
DCOT Aggregate 17 Commodities	0.44 (0.01)	0.70 (0.03)	0.58 (0.03)	0.41 (0.01)	0.65 (0.04)	0.50 (0.02)
Difference to Baseline		0.26 (0.23 - 0.30)	0.15 (0.11 - 0.19)	-0.03 (-0.05 - -0.01)	0.22 (0.17 - 0.26)	0.06 (0.03 - 0.10)
DCOT Aggregate 11 Commodities	0.43 (0.01)	0.69 (0.03)	0.49 (0.02)	0.39 (0.01)	0.56 (0.03)	0.70 (0.05)
Difference to Baseline		0.26 (0.23 - 0.29)	0.06 (0.03 - 0.09)	-0.04 (-0.06 - -0.03)	0.13 (0.09 - 0.17)	0.28 (0.21 - 0.36)

Note: The table displays the impact on the futures price. "baseline" refers to the total effect on the futures return due to the trading decisions of the trader groups. Technically, these are the coefficients of the last row of the matrix A^{-1} which equal all $1/\tilde{a}$ with $\tilde{a} = a^p + a^s + a^m + a^o + a^n$. The other columns report the price impact if one coefficient a^i corresponding to trader group i is set to zero in $\tilde{a}$. Standard errors are given in parentheses.

In a next step, we utilize the features of the model to infer the contribution of the trader groups' individual trading behavior on the futures return impact. We do so by computing the price impact $1/\tilde{a}^i$ that results by setting one coefficient a^i in $\tilde{a} = a^p + a^s + a^m + a^o + a^n$ to zero. Intuitively, this means that the corresponding trader group does not react to endogenous price variations stemming from trades of other market participants and thus has a perfectly inelastic demand. The results of this scenario for all trader groups are given in the remaining columns of the table. The impact on the futures return increases in case of all trader groups but money managers. Hence, if contrarian traders do not react to endogenous price movements caused by the trading of other market participants, then the futures price impact of demand shocks in commodity futures market rises significantly. In being the counterparty to trades, contrarian traders provide liquidity to other market participants and stabilize prices. This finding is in line with the theoretical literature on liquidity provision (Grossman and Miller, 1988, Campbell et al., 1993) and contrarian traders' role as market makers (Weill, 2007). The effect is most pronounced for producers and other reportable traders in the DCOT 17 aggregate and producers and non-

[10] To obtain standard errors for A^{-1} which is not a direct result from the maximum likelihood estimation where we can use the Hessian to derive standard errors, we proceed as follows. We first bootstrap the original model 1000 times and hence obtain 1000 different A-matrices. For each of these A-matrices we calculate its inverse and then apply the usual significance levels to the element-wise distribution of the A^{-1}-matrices. The bootstrap procedure is a standard residual based bootstrap with replacement.

reportables in the agricultural DCOT aggregate. The opposite is true for money managers who employ trend-following strategies: their trading amplifies price fluctuations in commodity futures markets, albeit being quantitatively comparatively small.

Table 2.4 reports the results for the same analysis for the SCOT aggregate of eleven agricultural commodities. The estimated baseline futures return impact of a one standard deviation change in the net long demand position of any trader group is slightly higher than in the DCOT models. This suggests that according to the SCOT data agricultural commodity futures markets are somewhat less liquid than found above when using the DCOT data. The decomposition of price contributions reveals the key role of commercials in providing liquidity and stabilizing prices in these markets: without them reacting to endogenous price movements, the futures return impact of demand shifts doubles. This effect halves for CITs and non-reportables, which is still quantitatively large when compared to the DCOT aggregate of agriculturals. Non-commercials again resemble money managers in the DCOT aggregate as their trading slightly amplifies price effects.

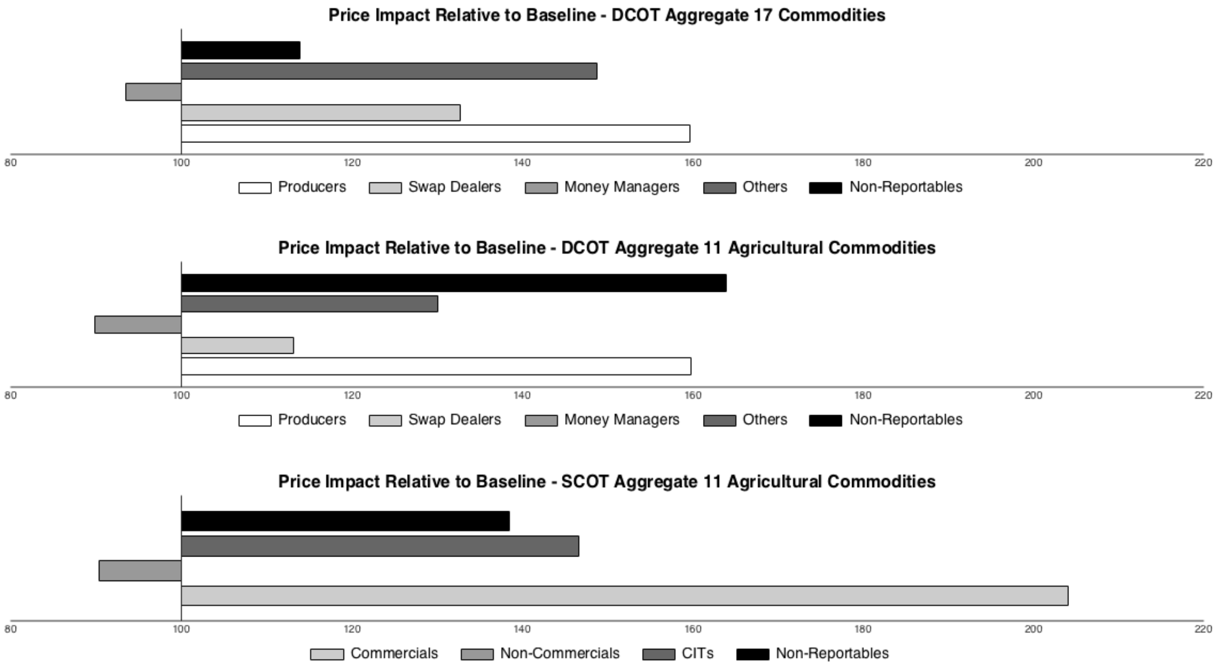
Table 2.4: Price Effects of Trading Strategies - SCOT Aggregate

	baseline	c	nc	cit	n
SCOT Aggregate 11 Commodities	0.54	1.10	0.49	0.79	0.74
	(0.01)	(0.06)	(0.02)	(0.05)	(0.05)
Difference to Baseline		0.53	-0.07	0.26	0.23
		(0.53 - 0.53)	(-0.07 - -0.07)	(0.26 - 0.26)	(0.23 - 0.23)

Note: The table displays the impact on the futures price. "baseline" refers to the total effect on the futures return due to the trading decisions of the trader groups. Technically, these are the coefficients of the last row of the matrix A^{-1} which equal all $1/\tilde{a}$ with $\tilde{a} = a^c + a^{nc} + a^{cit} + a^n$. The other columns report the price impact if one coefficient a^i corresponding to trader group i is set to zero in $\tilde{a}$. Standard errors are given in parentheses.

Figure 2.1 provides a graphical illustration of these effects and displays the percentage change of the return effect relative to the baseline model for the three aggregate models. Without contrarian traders being the counterpart to trades and thereby providing liquidity to other market participants, the futures return impact in commodity futures markets would increase significantly. Increases of 50% or more indicate that these effects would be economically sizeable and demonstrate how the price formation process in commodity futures markets would be affected if specific trader groups changed their trading behavior and stopped providing liquidity. In comparison, the price effects of money managers and non-commercials whose trend-following trading acts amplifying is comparatively small and raises price volatility only marginally. In the full DCOT aggregate it is producers and other reportables who take on the role as market makers, while in the agricultural DCOT aggregate small non-reportable traders seem to be crucial along producers. In the SCOT classification aggregate, commercials' trading is pivotal to the price formation process in agricultural commodity futures markets.

Figure 2.1: Comparison of Relative Price Impact Changes - Aggregate Core Models

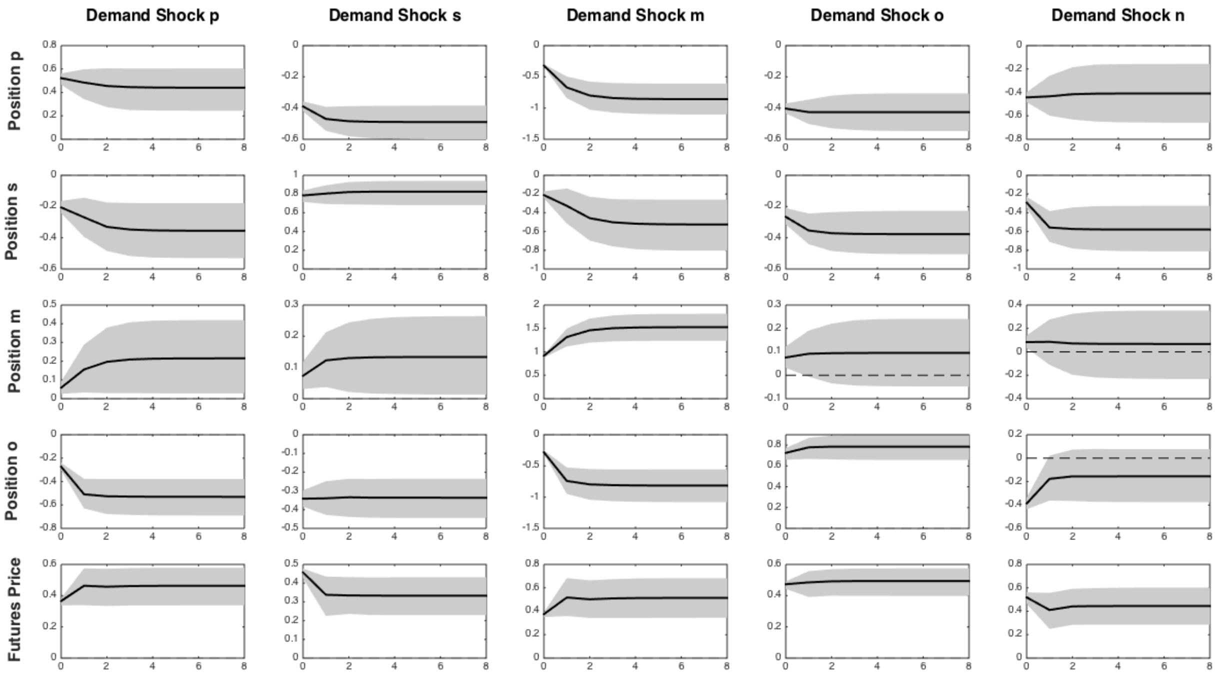


Note: The graphs show the percentage change in the aggregate futures price impact when factoring out the trading of one specific trader group for the three aggregate core models.

These results largely hold across almost all individual commodity futures markets for both trader classifications (see Table 2.9 as well as Figures 2.6 to 2.8 in Appendix 2.B). The following observations are worth mentioning. First, the somewhat heterogenous trading behavior of money managers across the different futures markets is also reflected in the price effects due to their trading. For instance, money managers' endogenous trading actually stabilizes the futures price of natural gas, while it raises the price volatility of coffee futures by more than found in the aggregate specifications. The latter is also true when turning to non-commercials in the SCOT trader classification: their amplifying price effect is strongest in the market for coffee. Second, comparing the markets for agricultural commodity futures with the ones for energy commodities and precious metals (DCOT classification) reveals that liquidity provision by swap dealers and other reportables tends to be of greater importance in the latter. This explains the difference in the two DCOT aggregate versions reported above and is in line with the observation that swap dealers carry out a substantially greater amount of non-index transactions in energy futures markets than in agricultural commodity futures markets (Irwin and Sanders, 2012). On the other hand, small non-reportable traders are less important in providing liquidity in energy and precious metal futures markets than in agricultural commodity markets.

So far we have analyzed price impact effects of demand shifts that can be traced back directly to the trading behavior of the different market participants. In the following we present cumulative impulse responses to assess dynamic effects and investigate the total effect of exogenous demand shifts on the futures price and the net long positions of trader groups. Figure 2.2 shows the cumulative impulse responses for the full DCOT aggregate encompassing all 17 commodities in our sample along with 90% bootstrapped confidence intervals.[11] The figure provides several conclusions. First, note that most impulse responses are significant with fairly small confidence intervals. Second, taking into account the group-specific demand shock variance given by the matrix B does not lead to marked differences in the price impact across the five demand shocks. Third, in response to a positive demand shock of any trader group (that is, an increase of their net long position), the futures price rises, contrarian traders decrease their net long position, and momentum traders increase their net long position. Finally, the figure provides evidence that most of the effects occur on impact and in the week thereafter, with only a limited role for dynamics, in particular of prices. This result is in line with asset prices and financial market participants responding instantaneously to each other and points towards the loss of information of other empirical approaches utilizing lead/lag relationships between variables for identification.

Figure 2.2: Cumulative Impulse Responses - DCOT 17 Commodities Aggregate

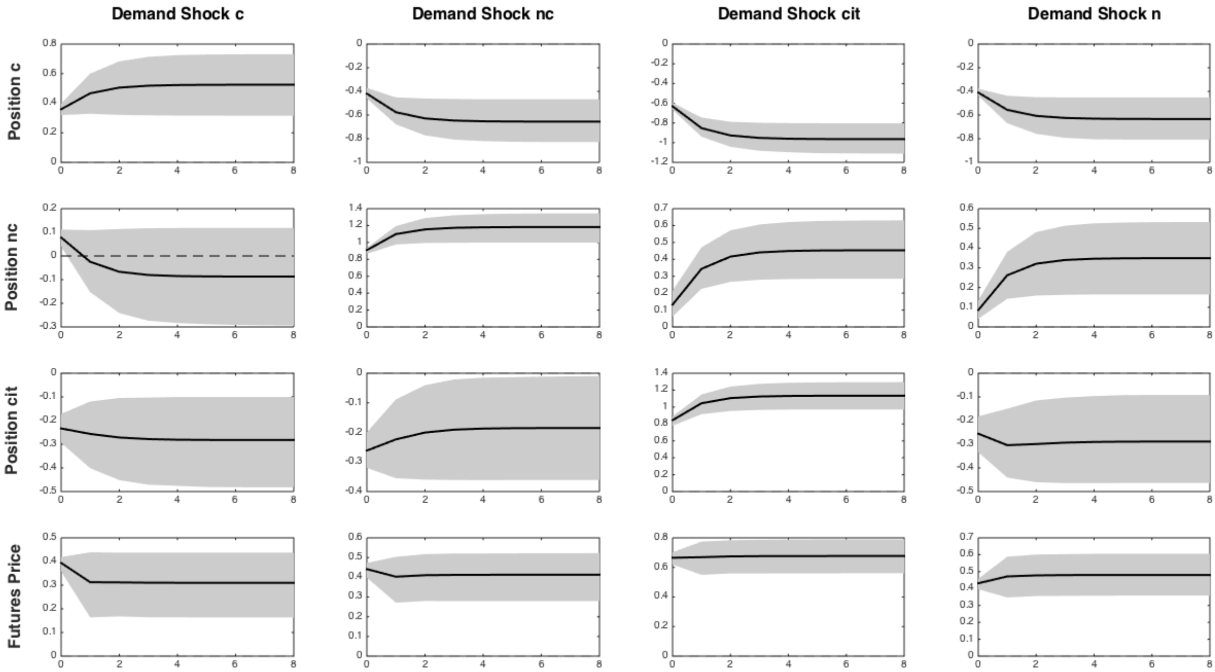


Note: The graphs show the cumulative impulse responses of the endogenous variables to traders' structural demand shocks in the DCOT aggregate encompassing 17 commodities. Shaded areas represent 90% confidence intervals based on 1000 bootstrapped replications using a standard residual based bootstrap with replacement. Vertical axes are in absolute changes in case of position variables and percentage changes in case of the futures price, horizontal axes are in weeks.

[11] Note that the impact value of the impulse response of the futures return is now given by elements in the last row of $C = A^{-1}B$ and thus differs from the values reported in the tables above that are solely based on A^{-1}. Further, the cumulative response for a given time horizon is the sum of all responses from the previous horizons until the current horizon. It therefore naturally stays persistent and is not expected to revert back to zero.

Figure 2.3 displays the cumulative impulse responses for the SCOT aggregate of eleven agricultural commodities. The figure features insights similar to the one above in terms of significance of responses and involved dynamics. Worth mentioning is the insignificant response of non-commercials to a demand shock of commercial traders. This implies that non-commercials who have been found to employ trend-following trading strategies might be willing to actually provide liquidity to other traders following a demand shift of commercials. In the agricultural DCOT aggregate (Figure 2.9 in Appendix 2.B), the momentum-trading money managers also do not exhibit a significant response to a demand shock of producers. However, in this specification swap dealers neither react significantly to producers nor money managers, too.

Figure 2.3: Cumulative Impulse Responses - SCOT 11 Agricultural Commodities Aggregate



Note: The graphs show the cumulative impulse responses of the endogenous variables to traders' structural demand shocks in the SCOT aggregate encompassing eleven agricultural commodities. Shaded areas represent 90% confidence intervals based on 1000 bootstrapped replications using a standard residual based bootstrap with replacement. Vertical axes are in absolute changes in case of position variables and percentage changes in case of the futures price, horizontal axes are in weeks.

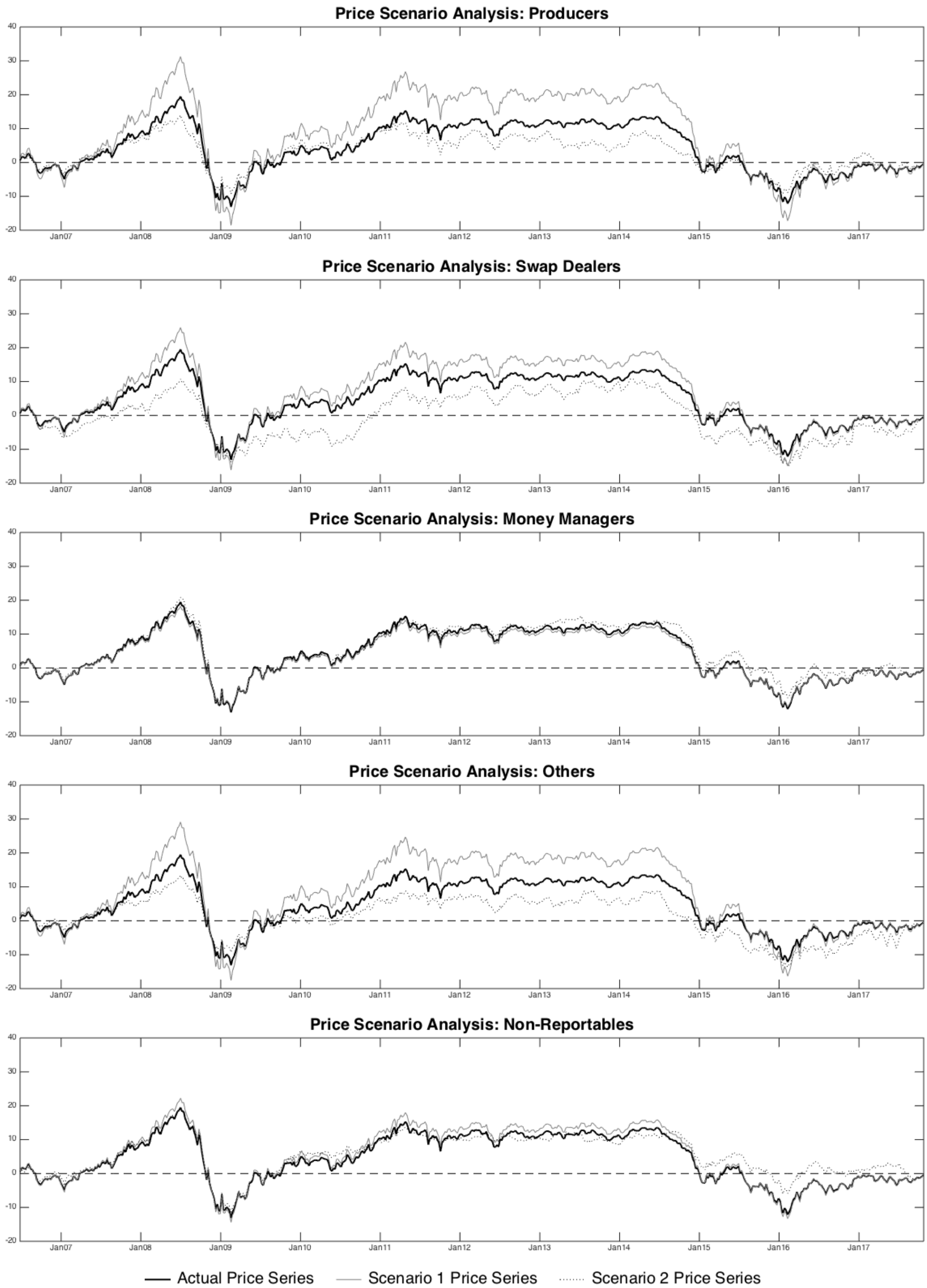
2.4.3 Liquidity Patterns over Time

In the final part of our analysis we investigate the overall effects of market participants' trading on the futures price over time. For this purpose note that trading can take place due to two different reasons. First, market participants react endogenously to price changes caused by trading incentives of other traders. Depending on whether they are contrarian or momentum traders they decrease/increase their position in response to an increase in prices following a purchase of the asset by another trader, and vice versa. In doing so, contrarian traders are providing liquidity, while momentum traders consume liquidity. Second, market participants also trade following their own purposes based on exogenous, private signals that prompt them to change their position in the market. In this case all traders, regardless whether employing contrarian or momentum strategies, are seeking for liquidity. Taken together, all trader groups are thus potentially providing as well as consuming liquidity in the futures market. In order to contrast the price effects of this two trading motives over time, we use the model to decompose the actual price movement into variation stemming from traders' endogenous response to price changes (scenario 1) and into variation caused by exogenous demand shifts (scenario 2). In the first scenario we repeat the analysis outlined above across time and look what happens to the price series if one trader group does not react to any futures price change. Intuitively, we can interpret this scenario as ceasing the liquidity provision of contrarian traders and the liquidity consumption of momentum traders, respectively. In the second scenario, we allow traders to react endogenously to any price change in the market, but remove price effects caused by exogenous demand shifts.[12] Note that for liquidity providers we should on average expect that the artificial price series lies above the actual price series in scenario 1 and below the actual price series in scenario 2. In case of momentum traders the reverse should be true on average.

Figure 2.4 and Figure 2.5 show the resulting artificial price series along with the actual price series for the full aggregate DCOT model and the SCOT aggregate of eleven agricultural commodities. In the graphs, the black thick line represents the actual commodity futures price series, which, as expected, lies in between the two artificial price series for most of the time. Regarding the overall DCOT aggregate including 17 commodities, we detect pronounced differences in the three price series for the trader groups of producers, swap dealers, and other reportables. The change in the futures price series in both scenarios is little for the two other trader groups, namely money managers and non-reportables, with somewhat more identifiable differences towards the end of the sample. In general, we observe that for contrarian traders the scenario 1 price series (gray line) lies above the actual price series, while the scenario 2 line (gray dotted line) lies below. For instance, with respect to scenario 1 our result implies that swap dealers which are mainly large banks were not able or willing to provide liquidity in 2007, from the second half of 2008 towards the end of 2009, as well as from 2015 onwards (Cheng et al., 2015, Bierbaumer et al., 2018). Interestingly, we also find that small non-reportable traders seem to have switched from being contrarian to momentum traders around mid 2014. In the SCOT aggregate model, the figure shows large effects in scenario 1 for commercials, pointing towards their pivotal role in the market. Effects are further pronounced for CITs and non-reportables, while being negligible for non-commercials. For example, regarding scenario 2, results imply that CITs and to lesser extent commercials and non-reportables were demanding liquidity in the market for most of the sample period. In both scenarios, price effects due to non-commercials are quite weak and hence are also in this case comparable to the group of money managers in the DCOT classification. Finally,

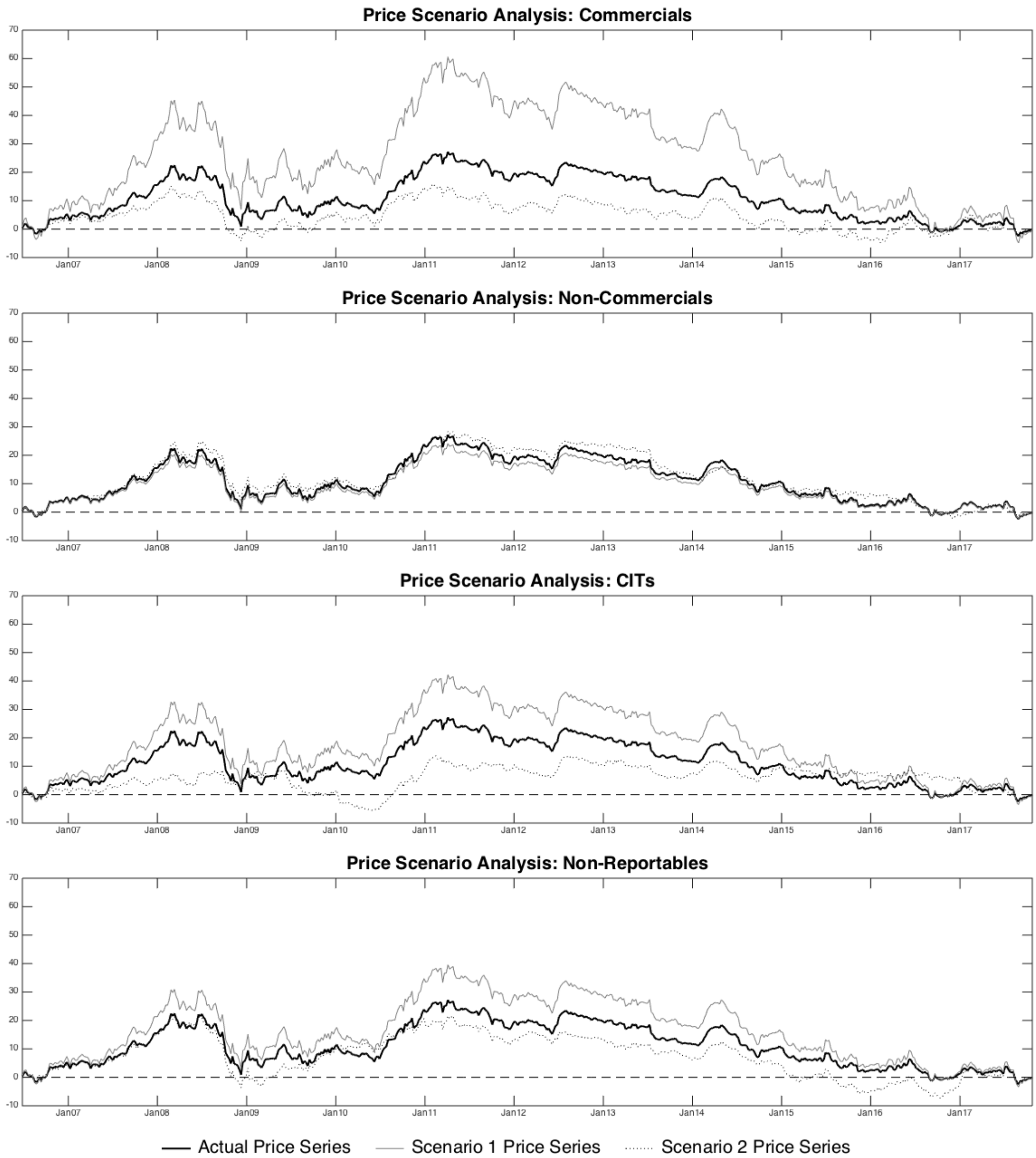
[12] Technically, in scenario 1 the demand slope coefficient a^i of one single trader group i is set to 0, while in scenario 2 the demand shock ϵ^i of one trader group i is set to 0.

Figure 2.4: Futures Price Decomposition - DCOT 17 Commodities Aggregate



Note: The graph shows the actual futures price series for the aggregate of 17 commodities along with computed price series under different scenarios. We use the model to decompose the actual price movement into variation stemming from traders' endogenous response to price changes (scenario 1) and into variation caused by exogenous demand shifts (scenario 2). Technically, in scenario 1 the demand slope coefficient a^i of one single trader group i is set to 0, while in scenario 2 the demand shock ϵ^i of one trader group i is set to 0.

Figure 2.5: Futures Price Decomposition - SCOT 11 Agricultural Commodities Aggregate



Note: The graph shows the actual futures price series for the aggregate of eleven agricultural commodities along with computed price series under different scenarios. We use the model to decompose the actual price movement into variation stemming from traders' endogenous response to price changes (scenario 1) and into variation caused by exogenous demand shifts (scenario 2). Technically, in scenario 1 the demand slope coefficient a^i of one single trader group i is set to 0, while in scenario 2 the demand shock ϵ^i of one trader group i is set to 0.

the figure suggests that CITs were just consuming liquidity in the market from 2015 onwards. Likewise, in the DCOT aggregate of eleven agricultural commodities we find a substantial role for producers and small non-reportable traders, as well as periods towards the end of the sample in which swap dealers, money managers, and other reportables, respectively, were only consuming liquidity (see Figure 2.10 in Appendix 2.B).[13]

Finally, in Table 2.5 we compare the variance of the different price series for the three aggregate baseline models. As expected, in most cases the variance of the actual price series lies between the variance of the two artificial price series. For contrarian traders the price variance increases in scenario 1 as they do not provide any liquidity, while it decreases in scenario 2 when removing their exogenously caused liquidity needs. The opposite is the case for momentum traders, that is, money managers in the DCOT specification and non-commercials in the SCOT specification. However, interestingly, the results indicate that in the overall DCOT aggregate of 17 commodities the price variance decreases in both scenarios with respect to money managers; a result driven by energy commodities (except heating oil) and copper.[14]

Table 2.5: Variance of Futures Price Series under Different Scenarios

DCOT Aggregate 17 Commodities	actual	p	s	m	o	n
Scenario 1	51.40	127.98	89.02	45.14	111.25	66.06
Scenario 2		23.88	44.58	49.49	34.23	33.53
DCOT Aggregate 11 Commodities						
Scenario 1	56.82	156.50	74.38	44.98	100.66	165.36
Scenario 2		28.88	45.61	64.14	39.28	27.68

SCOT Aggregate 11 Commodities	actual	c	nc	cit	n
Scenario 1	56.82	268.25	45.34	131.82	116.41
Scenario 2		23.22	67.28	17.87	53.81

Note: The table reports the variance of the actual aggregate commodity futures price series along with the variance of computed price series under different scenarios. We use the model to decompose the actual price movement into variation stemming from traders' endogenous response to price changes (scenario 1) and into variation caused by exogenous demand shifts (scenario 2). Technically, in scenario 1 the demand slope coefficient a^i of one single trader group i is set to 0, while in scenario 2 the the demand shock ϵ^i of one trader group i is set to 0.

2.4.4 Robustness Checks

Finally, we perform some robustness checks of our three aggregate baseline models. First, we shorten the estimation period to January 4, 2011, until July 1, 2014, to exclude periods of large price increases and decreases, respectively, of the three aggregate futures price series at the beginning and the end of the sample. Second, we add the surprise component in news releases of 30 U.S. macroeconomic indicators as additional exogenous variables. Third, we exclude the

[13] Graphs for the individual commodity futures markets are available upon request.
[14] Results for the individual commodity futures markets are also available upon request.

two exogenous variables (number of initial jobless claims and the balance sheet of the Fed) from the baseline specification. Fourth, we allow for four lags in the models.

Table 2.10 in Appendix 2.B contains the estimated demand curve slope coefficients of these alterations. They are qualitatively and mostly quantitatively similar to the baseline estimates, which are repeated in the first row of each model for comparison. Quantitatively, the largest difference in the estimated net long demand coefficients in comparison to the baseline specification occurs in the robustness check of the two DCOT model aggregates featuring the shorter sample period. With regards to the full DCOT aggregate of 17 commodities, these results suggest that swap dealers were more willing or able to absorb trades from other market participants as indicated by a larger a-coefficient in this sub-period, while money managers were also more price-elastic in their trend-following strategy. Taken as a whole, the main results appear to be robust to these alterations of the model and the data.

2.5 Conclusion

A large part of the finance literature commonly uses single equation models to study the trading behavior of different market participants and its implications for market outcomes. In this paper we propose a simple multivariate econometric framework for structurally estimating the trading strategies of different trader groups in a given asset market. Rather than relying on lead-lag relationships for identification, we formulate a stylized theoretical model that provides enough restrictions for the identification of its empirical counterpart. We model each group's demand function depending on the contemporaneous asset price and a group-specific demand shock within a system of simultaneous equations. We apply the methodology to commodity futures markets, using two different publicly available datasets. Our results show that most trader groups employ contrarian strategies, meaning that they decrease their net long exposure when prices rise, providing liquidity to other traders and stabilizing prices. In contrast, money managers and non-commercials follow momentum strategies, consuming liquidity when prices increase and raising volatility.

Our framework makes use of methodologies that are widely used mainly in the macroeconomic literature and that have been developed to address problems of simultaneity. It can enhance single equation models where identification is typically achieved via lead lag relationships along two dimensions. First, it allows modeling contemporaneous relationship between prices and positions. This is particularly relevant given the development of financial markets with electronic and algorithmic trading where market participants respond to price developments in essentially continuous time. Second, the approach facilitates a decomposition of observed price dynamics into the contributions of different trader groups and their trading strategies.

2.A Data Appendix

Table 2.6: Definition of Variables

Variable	Definition and Source
Position of Trader Groups	Net long position of a trader group in one specific commodity futures market. Standardized first absolute differences. U.S. Commodity Futures Trading Commission (CFTC), Disaggregated Commitments of Traders (DCOT) Report and Supplemental Commitments of Traders Report. The trader groups are "Producer/Merchant/Processor/User," "Swap Dealers," "Money Managers," "Other Reportables," and "Non-Reportables" in case of the DCOT Report and "Commercials," "Non-Commercials," "CITs," and "Non-Reportables" in case of the SCOT Report. The commodity futures markets considered are wheat SRW (Chicago Board of Trade), wheat HRW (Kansas City Board of Trade), corn (Chicago Board of Trade), soybeans (Chicago Board of Trade), cotton no. 2 (New York Board of Trade), lean hogs (Chicago Mercantile Exchange), live cattle (Chicago Mercantile Exchange), feeder cattle (Chicago Mercantile Exchange), cocoa (New York Board of Trade), sugar no. 11 (New York Board of Trade), coffee C (New York Board of Trade) - for both DCOT and SCOT position data - and crude oil, light sweet (New York Mercantile Exchange), no. 2 heating oil (New York Mercantile Exchange), gasoline blendstock RBOB (New York Mercantile Exchange), natural gas (New York Mercantile Exchange), copper-grade #1 (Commodity Exchange Inc.), and silver (Commodity Exchange Inc.) - for DCOT position data only.
Commodity Futures Prices	Continuous futures settlement price ('PX_SETTLE') of a respective commodity. Standardized first log-differences. Bloomberg. These are wheat SRW (Chicago Board of Trade, Bloomberg symbol: 'W 1 Comdty'), KC wheat HRW (Kansas City Board of Trade, 'KW 1 Comdty'), corn (Chicago Board of Trade, 'C 1 Comdty'), soybeans (Chicago Board of Trade, 'S 1 Comdty'), cotton no. 2 (Intercontinental Exchange, 'CT1 Comdty'), lean hogs (Chicago Mercantile Exchange, 'LH1 Comdty'), live cattle (Chicago Mercantile Exchange, 'LC1 Comdty'), feeder cattle (Chicago Mercantile Exchange, 'FC1 Comdty'), cocoa (Intercontinental Exchange, 'CC1 Comdty'), sugar no. 11 (Intercontinental Exchange, 'SB1 Comdty'), coffee C (Intercontinental Exchange, 'KC1 Comdty'), WTI crude oil (New York Mercantile Exchange, 'CL1 Comdty'), heating oil no. 2 (New York Mercantile Exchange, 'HO1 Comdty'), RBOB gasoline (New York Mercantile Exchange, 'XB1 Comdty'), natural gas (New York Mercantile Exchange, 'NG1 Comdty'), copper-grade #1 (Commodity Exchange Inc., 'HG1 Comdty'), silver (Commodity Exchange Inc., 'SI1 Comdty').
Initial Jobless Claims	Number Initial Claims, Weekly, Ending Saturday, Seasonally Adjusted. Standardized first log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: ICSA.
Fed Total Assets	All Federal Reserve Banks Total Assets, Millions of Dollars, Weekly, as of Wednesday, Not Seasonally Adjusted. Standardized first log-differences. Federal Reserve Economic Data, St. Louis Fed. Series code: WALCL.
U.S. Macroeconomic Surprise Indicators	Difference between actual release and the median forecast estimate of economists surveyed by Bloomberg. Indicators: American Consumer Spending Growth Rates MoM SA (PCE CRCH:IND), Average Hourly Earnings MoM% SA (AHE MOM%:IND), Average Hourly Earnings YoY% SA (AHE YOY%:IND), Business Inventories MoM SA (MTIBCHNG:IND), Capacity Utilization % of Total Capacity (CPTICHNG:IND), Conference Board Leading Indicators MoM (LEI CHNG:IND), Construction Spending Total MoM SA (CNSTTMOM:IND), Core Producer Price Index (PPI XYOY:IND), CPI Urban Consumers Less Food & Energy YoY NSA (CPI XYOY:IND), CPI Urban Consumers MoM SA (CPI CHNG:IND), CPI Urban Consumers YoY NSA (CPI YOY:IND), Durable Goods New Orders Industries MoM SA (DGNOCHNG:IND), GDP Chained 2009 Dollars QoQ SAAR (GDP CQOQ:IND), Housing Starts/Permits (NHSPSTOT:IND), Industrial Production MoM 2007=100 SA (IP CHNG:IND), Initial Jobless Claims SA (INJCJC:IND), Markit Manufacturing PMI SA (MPMIUSMA:IND), Markit Services PMI Business Activity SA (MPMIUSSA:IND), Nonfarm Payrolls Total MoM SA (NFP TCH:IND), Personal Consumption Expenditure CPI YoY SA (PCE CYOY:IND), Personal Income MoM SA (PITLCHNG:IND), PPI Final Demand MoM SA (PCE CYOY:IND), PPI Finished Goods SA MoM% (PPI CHNG:IND), Producer Price

Index - Finished Goods (PPI YOY:IND), Productivity Output Per Hour Nonfarm Business Sector QoQ SA (PRODNFR%:IND), Retail Sales (Less Auto and Gas Stations) SA MoM% Change (RSTAXAG%:IND), Trade Balance of Goods and Services SA (USTBTOT:IND), Unit Labor Costs Nonfarm Business Sector QoQ% SAAR (COSTNFR%:IND), University of Michigan Consumer Confidence Indicator (CONSSENT:IND), US Government Budget Balance FED (FDDSSD:IND)

Definitions of Trader Groups in DCOT Reports

Below are the definitions of the four trader groups in the DCOT Reports as stated in CFTC (2018a). The fifth group of "Non-Reportables" is a residual component.

Producer/Merchant/Processor/User
An entity that predominantly engages in the production, processing, packing or handling of a physical commodity and uses the futures markets to manage or hedge risks associated with those activities.

Swap Dealer
An entity that deals primarily in swaps for a commodity and uses the futures markets to manage or hedge the risk associated with those swaps transactions. The swap dealer's counterparties may be speculative traders, like hedge funds, or traditional commercial clients that are managing risk arising from their dealings in the physical commodity.

Money Manager
A registered commodity trading advisor (CTA); a registered commodity pool operator (CPO); or an unregistered fund identified by CFTC. These traders are engaged in managing and conducting organized futures trading on behalf of clients.

Other Reportables
Every other reportable trader that is not placed into one of the other three categories is placed into the "other reportables" category.

Non-Reportables
The remainder of total open interest in the specific futures market that is not accounted for by the other four categories of traders.

Definitions of Trader Groups in SCOT Reports

Below are the definitions of the three trader groups in the SCOT Reports as stated in CFTC (2018b). The fourth group of "Non-Reportables" is a residual component.

Commercials vs. Non-Commercials
All of a trader's reported futures positions in a commodity are classified as commercial if the trader uses futures contracts in that particular commodity for hedging as defined in CFTC Regulation 1.3, 17 CFR 1.3(z). A trading entity generally gets classified as a "commercial" trader by filing a statement with the Commission, on CFTC Form 40: Statement of Reporting Trader, that it is commercially "...engaged in business activities hedged by the use of the futures or option markets."

Commodity Index Traders
These traders are drawn from the noncommercial and commercial categories. The noncommercial category includes positions of managed funds, pension funds, and other investors that are generally seeking exposure to a broad index of commodity prices as an asset class in an unleveraged and passively-managed manner. The commercial category includes positions for entities whose trading predominantly reflects hedging of over-the-counter transactions involving commodity indices - for example, a swap dealer holding long futures positions to hedge a short commodity index exposure opposite institutional traders, such as pension funds. All of these traders - whether coming from the noncommercial or commercial categories - are generally replicating a commodity index by establishing long futures positions in the component markets and then rolling those positions forward from future to future using a fixed methodology.

Non-Reportables
The remainder of total open interest in the specific futures market that is not accounted for by the other four categories of traders.

Table 2.7: Yearly S&P GSCI Weights Employed in the Aggregation

17 Commodities Aggregate

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Wheat SRW	0.03	0.04	0.05	0.06	0.06	0.05	0.05	0.05	0.05	0.05	0.05	0.05
Wheat HRW	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01
Corn	0.03	0.04	0.05	0.06	0.06	0.06	0.08	0.07	0.07	0.06	0.06	0.08
Soybeans	0.02	0.02	0.03	0.04	0.04	0.04	0.04	0.04	0.04	0.05	0.05	0.05
Cotton	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02	0.02	0.02	0.02	0.02
Lean hogs	0.02	0.02	0.01	0.02	0.02	0.02	0.02	0.02	0.03	0.03	0.04	0.04
Live cattle	0.03	0.03	0.03	0.04	0.04	0.03	0.04	0.04	0.05	0.06	0.07	0.07
Feeder cattle	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Cocoa	0.00	0.00	0.00	0.01	0.01	0.00	0.00	0.00	0.00	0.01	0.01	0.01
Sugar	0.02	0.01	0.01	0.03	0.03	0.04	0.03	0.03	0.02	0.02	0.02	0.04
Coffee	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.01	0.02
WTI crude oil	0.44	0.44	0.49	0.44	0.44	0.47	0.42	0.43	0.39	0.36	0.35	0.34
Heating oil	0.10	0.07	0.07	0.05	0.05	0.06	0.09	0.09	0.10	0.09	0.08	0.06
RBOB gasoline	0.05	0.05	0.06	0.05	0.05	0.06	0.08	0.08	0.10	0.09	0.08	0.07
Natural gas	0.10	0.09	0.09	0.07	0.07	0.04	0.03	0.04	0.05	0.05	0.05	0.05
Copper	0.12	0.13	0.09	0.09	0.09	0.05	0.05	0.05	0.05	0.06	0.06	0.06
Silver	0.00	0.00	0.00	0.01	0.01	0.01	0.01	0.01	0.00	0.01	0.01	0.01

11 Agricultural Commodities Aggregate

	2006	2007	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017
Wheat SRW	0.17	0.20	0.22	0.20	0.20	0.16	0.15	0.17	0.17	0.15	0.14	0.15
Wheat HRW	0.06	0.07	0.05	0.04	0.04	0.04	0.05	0.04	0.04	0.04	0.04	0.04
Corn	0.16	0.18	0.21	0.20	0.20	0.22	0.22	0.24	0.22	0.18	0.17	0.21
Soybeans	0.09	0.11	0.13	0.14	0.14	0.12	0.12	0.14	0.14	0.13	0.12	0.15
Cotton	0.06	0.05	0.05	0.04	0.04	0.08	0.08	0.05	0.05	0.05	0.05	0.06
Lean hogs	0.10	0.08	0.07	0.08	0.08	0.07	0.07	0.08	0.09	0.10	0.09	0.10
Live cattle	0.15	0.15	0.13	0.14	0.14	0.12	0.11	0.13	0.15	0.18	0.20	0.19
Feeder cattle	0.04	0.03	0.02	0.03	0.03	0.02	0.02	0.03	0.03	0.04	0.06	0.05
Cocoa	0.01	0.01	0.01	0.02	0.02	0.01	0.01	0.01	0.01	0.02	0.02	0.02
Sugar	0.11	0.06	0.07	0.09	0.09	0.11	0.11	0.08	0.07	0.07	0.07	0.10
Coffee	0.05	0.04	0.04	0.04	0.04	0.05	0.05	0.04	0.03	0.04	0.04	0.04

Note: The table reports the yearly S&P GSCI weights employed in the aggregation of the position data and the futures price for the three aggregate core models.

2.B Further Tables and Figures

Table 2.8: Net Long Demand Curve Slope Coefficients - Individual Commodities

	DCOT report classification					SCOT report classification			
	a^p	a^s	a^m	a^o	a^n	a^c	a^{nc}	a^{cit}	a^n
Wheat SRW	0.90	0.44	-0.24	0.81	0.36	0.97	-0.13	0.79	0.37
	(0.04)	(0.06)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.09)	(0.04)
Wheat HRW	0.79	0.38	-0.14	0.49	0.75	0.86	-0.04	0.63	0.50
	(0.04)	(0.06)	(0.04)	(0.06)	(0.06)	(0.04)	(0.05)	(0.09)	(0.04)
Corn	0.87	0.38	-0.22	0.49	0.88	0.95	-0.15	0.73	0.46
	(0.03)	(0.06)	(0.04)	(0.06)	(0.08)	(0.04)	(0.04)	(0.09)	(0.05)
Soybeans	0.88	0.35	-0.31	0.46	1.05	0.97	-0.23	0.61	0.61
	(0.03)	(0.06)	(0.04)	(0.06)	(0.09)	(0.04)	(0.04)	(0.09)	(0.05)
Cotton	0.79	0.53	-0.10	0.36	0.73	0.90	-0.03	0.66	0.47
	(0.04)	(0.06)	(0.04)	(0.06)	(0.06)	(0.05)	(0.05)	(0.08)	(0.04)
Lean hogs	0.68	0.42	0.06	0.57	0.53	0.76	0.17	0.60	0.43
	(0.04)	(0.06)	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.08)	(0.04)
Live cattle	0.75	0.35	0.01	0.52	0.68	0.86	0.13	0.47	0.52
	(0.04)	(0.05)	(0.04)	(0.06)	(0.05)	(0.05)	(0.05)	(0.07)	(0.04)
Feeder cattle	0.70	0.46	0.00	0.49	0.76	0.80	0.09	0.59	0.68
	(0.05)	(0.05)	(0.04)	(0.06)	(0.07)	(0.05)	(0.05)	(0.07)	(0.07)
Cocoa	0.82	0.53	-0.21	0.51	0.57	0.88	-0.13	0.85	0.37
	(0.03)	(0.06)	(0.04)	(0.06)	(0.05)	(0.04)	(0.04)	(0.11)	(0.04)
Sugar	0.84	0.81	-0.21	0.42	0.42	0.96	-0.15	0.85	0.29
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)	(0.04)	(0.05)	(0.09)	(0.04)
Coffee	0.90	0.63	-0.52	0.47	0.88	0.95	-0.48	0.95	0.54
	(0.03)	(0.06)	(0.03)	(0.06)	(0.09)	(0.03)	(0.03)	(0.13)	(0.05)
WTI crude oil	0.75	0.60	-0.15	0.76	0.26				
	(0.06)	(0.05)	(0.04)	(0.06)	(0.04)				
Heating oil	0.87	0.69	-0.14	0.68	0.21				
	(0.04)	(0.06)	(0.04)	(0.05)	(0.06)				
RBOB gasoline	0.83	0.55	-0.03	0.67	0.36				
	(0.05)	(0.06)	(0.05)	(0.05)	(0.06)				
Natural gas	0.73	0.32	0.17	0.88	0.17				
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)				
Copper	0.78	0.72	-0.09	0.79	0.13				
	(0.04)	(0.06)	(0.04)	(0.05)	(0.06)				
Silver	0.81	0.82	-0.15	0.71	-0.03				
	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)				

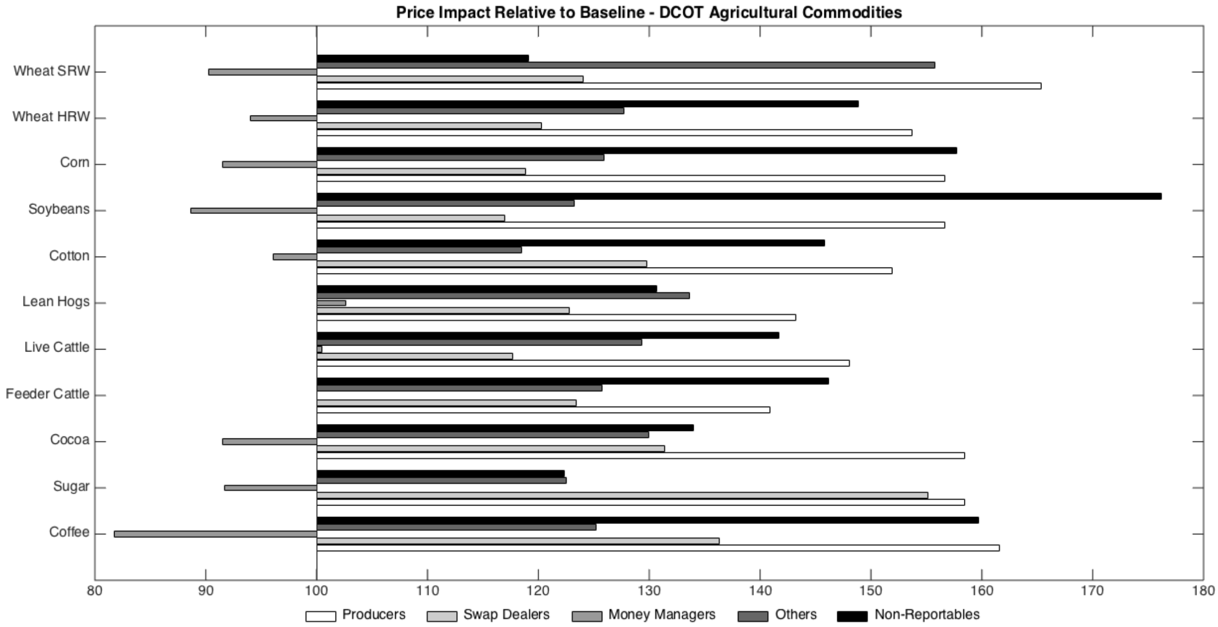
Note: The table shows the estimated net long demand curve slope estimates for the different trader groups across different commodity futures markets. Standard errors are given in parentheses.

Table 2.9: Price Effects of Trading Strategies - Individual Commodities

	DCOT report classification						SCOT report classification				
	base	p	s	m	o	n	base	c	nc	cit	n
Wheat SRW	0.44	0.73	0.55	0.40	0.69	0.53	0.50	0.97	0.47	0.82	0.61
	(0.01)	(0.03)	(0.03)	(0.01)	(0.04)	(0.02)	(0.01)	(0.03)	(0.02)	(0.07)	(0.03)
Wheat HRW	0.44	0.68	0.53	0.41	0.56	0.66	0.51	0.92	0.50	0.76	0.69
	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.05)	(0.01)	(0.04)	(0.02)	(0.05)	(0.04)
Corn	0.42	0.65	0.50	0.38	0.52	0.66	0.50	0.96	0.47	0.79	0.66
	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.04)	(0.01)	(0.04)	(0.02)	(0.07)	(0.04)
Soybeans	0.41	0.64	0.48	0.36	0.51	0.72	0.51	1.01	0.46	0.74	0.74
	(0.01)	(0.03)	(0.02)	(0.01)	(0.02)	(0.05)	(0.01)	(0.04)	(0.01)	(0.05)	(0.05)
Cotton	0.43	0.65	0.56	0.41	0.51	0.63	0.50	0.92	0.49	0.75	0.65
	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.05)	(0.01)	(0.05)	(0.02)	(0.04)	(0.04)
Lean hogs	0.44	0.63	0.54	0.45	0.59	0.58	0.51	0.83	0.56	0.73	0.65
	(0.01)	(0.02)	(0.02)	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)	(0.04)	(0.03)
Live cattle	0.43	0.64	0.51	0.43	0.56	0.61	0.50	0.88	0.54	0.66	0.68
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.04)	(0.02)	(0.03)	(0.03)
Feeder cattle	0.41	0.58	0.51	0.41	0.52	0.60	0.46	0.74	0.48	0.64	0.68
	(0.01)	(0.02)	(0.02)	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)	(0.04)	(0.04)
Cocoa	0.45	0.71	0.59	0.41	0.58	0.60	0.51	0.92	0.48	0.89	0.63
	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.03)	(0.01)	(0.05)	(0.02)	(0.08)	(0.03)
Sugar	0.44	0.70	0.68	0.40	0.54	0.54	0.51	1.01	0.48	0.91	0.60
	(0.01)	(0.03)	(0.03)	(0.01)	(0.02)	(0.02)	(0.01)	(0.04)	(0.02)	(0.06)	(0.02)
Coffee	0.43	0.69	0.58	0.35	0.53	0.68	0.51	0.99	0.41	1.00	0.70
	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.06)	(0.02)	(0.07)	(0.02)	(0.11)	(0.06)
WTI crude oil	0.45	0.68	0.61	0.42	0.68	0.51					
	(0.01)	(0.03)	(0.02)	(0.01)	(0.03)	(0.01)					
Heating oil	0.43	0.70	0.62	0.41	0.61	0.48					
	(0.01)	(0.02)	(0.03)	(0.01)	(0.03)	(0.02)					
RBOB gasoline	0.42	0.65	0.55	0.41	0.58	0.49					
	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.02)					
Natural gas	0.44	0.65	0.51	0.48	0.72	0.47					
	(0.01)	(0.03)	(0.02)	(0.02)	(0.03)	(0.01)					
Copper	0.43	0.64	0.62	0.41	0.65	0.45					
	(0.01)	(0.03)	(0.03)	(0.01)	(0.03)	(0.01)					
Silver	0.46	0.74	0.74	0.43	0.69	0.45					
	(0.01)	(0.05)	(0.05)	(0.01)	(0.05)	(0.01)					

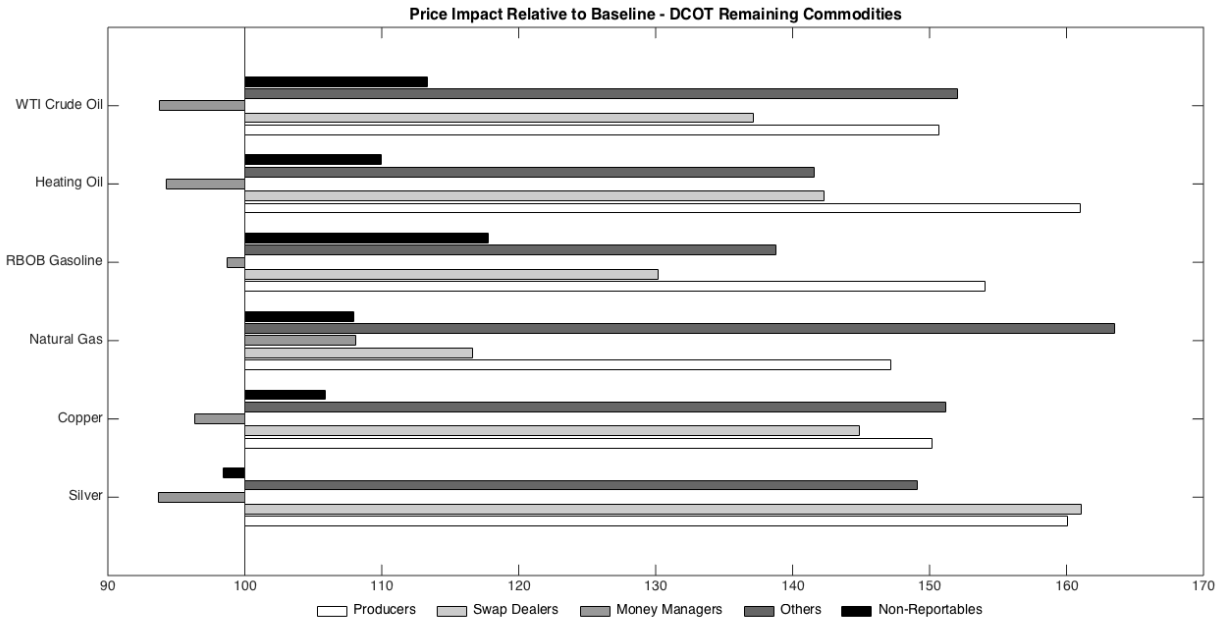
Note: The table displays the impact on the futures price. "baseline" refers to the total effect on the futures return due to the trading decisions of the trader groups. Technically, these are the coefficients of the last row of the matrix A^{-1} which equal all $1/\tilde{a}$ with $\tilde{a} = a^p + a^s + a^m + a^o + a^n$ in case of the DCOT report classification and $1/\tilde{a}$ with $\tilde{a} = a^c + a^{nc} + a^{cit} + a^n$ in case of the SCOT report classification, respectively. The other columns report the price impact if one coefficient a^i corresponding to trader group i is set to zero in $\tilde{a}$. Standard errors are given in parentheses.

Figure 2.6: Comparison of Relative Price Impact Changes - DCOT Agricultural Commodities



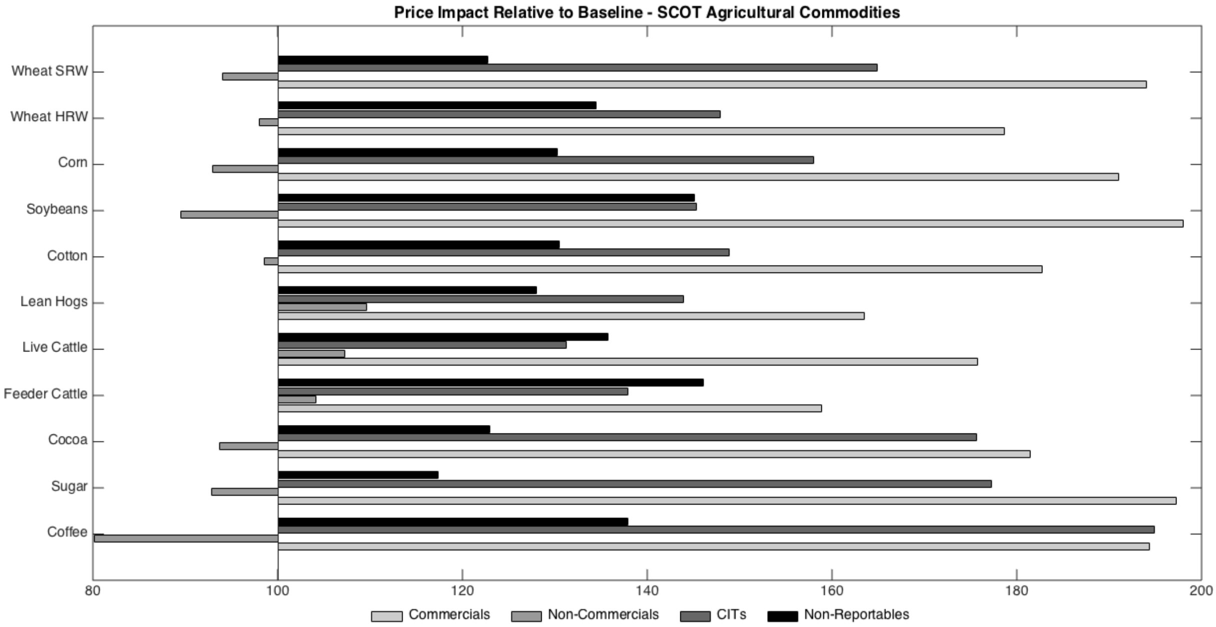
Note: The graph shows the relative change in the futures price impact when factoring out the trading of one specific trader group under the DCOT report classification for eleven agricultural commodities.

Figure 2.7: Comparison of Relative Price Impact Changes - DCOT Remaining Commodities



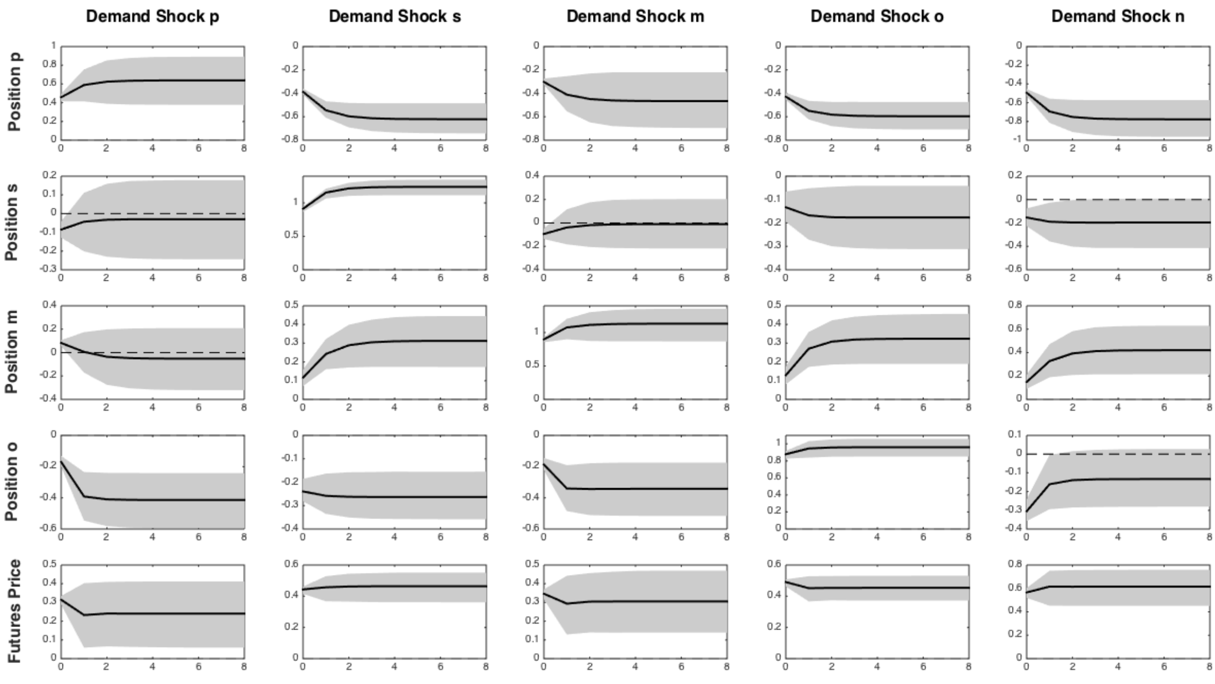
Note: The graph shows the relative change in the futures price impact when factoring out the trading of one specific trader group under the DCOT report classification for seven energy and precious metal commodities.

Figure 2.8: Comparison of Relative Price Impact Changes - SCOT Agricultural Commodities



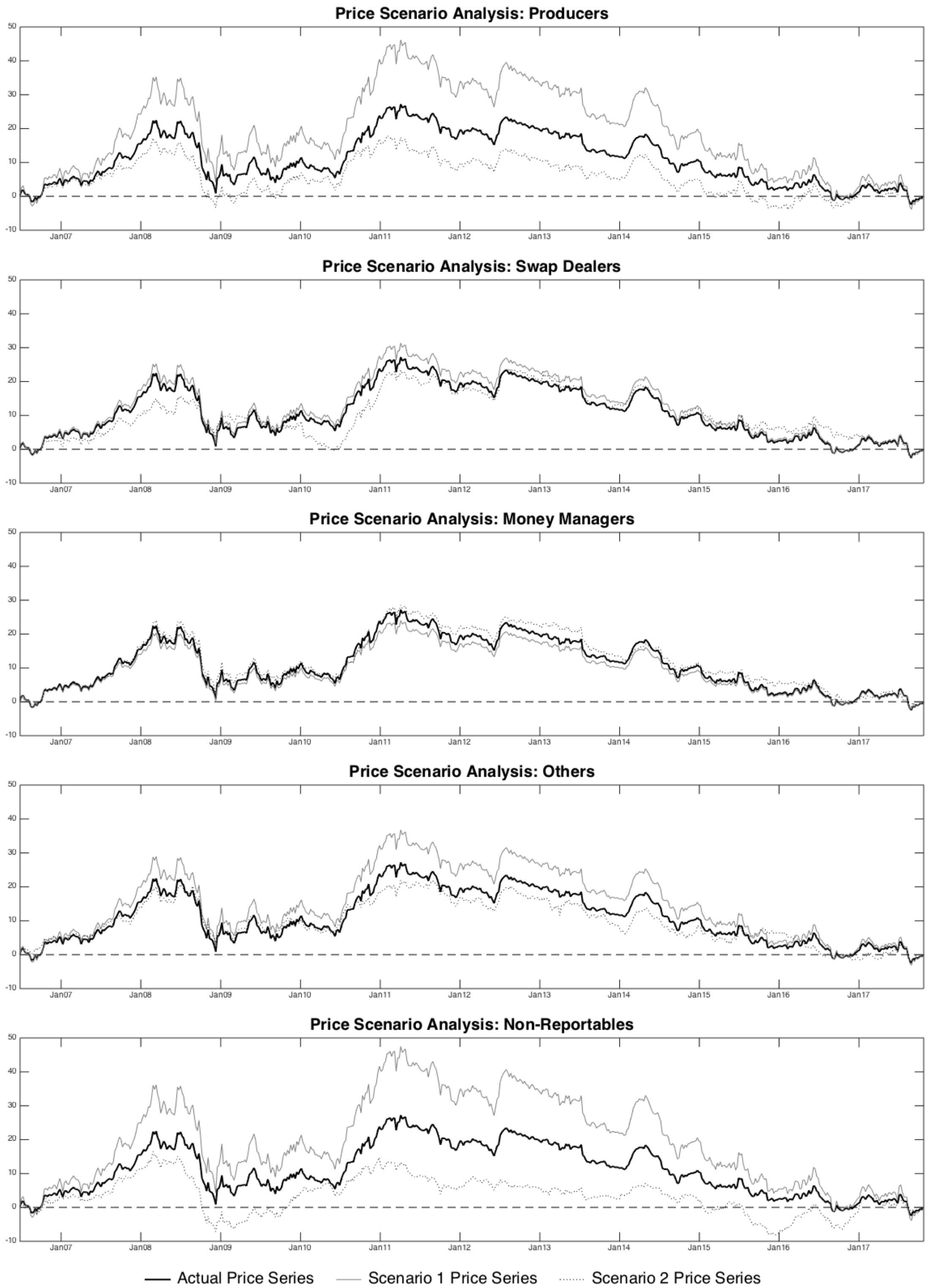
Note: The graph shows the relative change in the futures price impact when factoring out the trading of one specific trader group under the SCOT report classification for eleven agricultural commodities.

Figure 2.9: Cumulative Impulse Responses - DCOT 11 Agricultural Commodities Aggregate



Note: The graphs show the cumulative impulse responses of the endogenous variables to traders' structural demand shocks in the DCOT aggregate encompassing eleven agricultural commodities. Shaded areas represent 90% confidence intervals based on 1000 bootstrapped replications using a standard residual based bootstrap with replacement. Vertical axes are in absolute changes in case of position variables and percentage changes in case of the futures price, horizontal axes are in weeks.

Figure 2.10: Futures Price Decomposition - DCOT 11 Agricultural Commodities Aggregate



Note: The graph shows the actual futures price series for the aggregate of eleven agricultural commodities along with computed price series under different scenarios. We use the model to decompose the actual price movement into variation stemming from traders' endogenous response to price changes (scenario 1) and into variation caused by exogenous demand shifts (scenario 2). Technically, in scenario 1 the demand slope coefficient a^i of one single trader group i is set to 0, while in scenario 2 the demand shock ϵ^i of one trader group i is set to 0.

Table 2.10: Sensitivity Analysis - Aggregate Core Models

DCOT Aggregate 17 Commodities	p	s	m	o	n
Baseline	0.85	0.56	-0.16	0.75	0.28
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)
Shorter sample period	0.88	0.76	-0.39	0.81	0.12
	(0.06)	(0.09)	(0.06)	(0.10)	(0.13)
Additional exogenous variables	0.86	0.54	-0.15	0.74	0.31
	(0.04)	(0.05)	(0.04)	(0.06)	(0.07)
No exogenous variables	0.85	0.55	-0.16	0.74	0.28
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)
Four lags	0.85	0.57	-0.17	0.74	0.26
	(0.04)	(0.05)	(0.04)	(0.06)	(0.06)

DCOT Aggregate 11 Commodities	p	s	m	o	n
Baseline	0.87	0.27	-0.26	0.54	0.91
	(0.03)	(0.05)	(0.04)	(0.06)	(0.08)
Shorter sample period	0.88	0.33	-0.27	0.72	0.64
	(0.07)	(0.09)	(0.07)	(0.11)	(0.13)
Additional exogenous variables	0.87	0.28	-0.27	0.54	0.93
	(0.03)	(0.05)	(0.04)	(0.06)	(0.08)
No exogenous variables	0.86	0.26	-0.25	0.53	0.93
	(0.03)	(0.05)	(0.04)	(0.06)	(0.08)
Four lags	0.86	0.27	-0.25	0.57	0.87
	(0.03)	(0.05)	(0.04)	(0.06)	(0.08)

SCOT Aggregate 11 Commodities	c	nc	cit	n
Baseline	0.95	-0.20	0.59	0.52
	(0.04)	(0.04)	(0.09)	(0.04)
Shorter sample period	0.96	-0.16	0.51	0.55
	(0.07)	(0.08)	(0.15)	(0.08)
Additional exogenous variables	0.95	-0.21	0.61	0.53
	(0.04)	(0.04)	(0.09)	(0.04)
No exogenous variables	0.94	-0.19	0.58	0.53
	(0.04)	(0.04)	(0.09)	(0.04)
Four lags	0.95	-0.18	0.58	0.49
	(0.04)	(0.04)	(0.08)	(0.04)

Note: The table reports the estimated net long demand curve slope estimates for the different trader groups in robustness checks of the three aggregate core models. For ease of comparison, the first row in each sub-table contains the results of the baseline specification. Standard errors are given in parentheses.

CHAPTER 3

Macroeconomic Effects of Loan Supply Shocks: Distinguishing Between Business and Household Loans

3.1 Introduction

The global financial crisis of 2007 to 2009 has revived the interest in the role played by financial intermediaries in driving business cycles. Prior to the crisis, financial intermediaries and credit markets in general were believed to mainly propagate and amplify real macroeconomic shocks. Financial frictions in theoretical models have been modeled to manifest themselves through shocks to the demand side of credit. The financial crisis has questioned this view as it demonstrated that supply shocks originating within the financial sector can exert a non-negligible effect on the macroeconomy on their own. Given the observed drop and shortage in the supply of loans to the private non-financial sector during the crisis, the empirical identification and assessment of loan supply shocks has become a key issue.[1] Despite being studied in some recent contributions (Hristov et al., 2012, Bassett et al., 2014, Bijsterbosch and Falagiarda, 2015, Gambetti and Musso, 2017, Furlanetto et al., forthcoming, among others) and broad consensus on their general macroeconomic relevance, there remain open questions about their transmission mechanisms to the real economy and whether there are differences depending on which sector is affected.

In this paper, I distinguish loan supply shocks affecting the business sector from those affecting the household sector in one structural vector autoregressive (VAR) model for the U.S. and study their effects by considering several macroeconomic variables. The majority of empirical contributions so far - be it microeconometric or macroeconometric - has either focused on lending to the whole private non-financial sector or solely on one sector. For example, with respect to macroeconometric time series studies, Bijsterbosch and Falagiarda (2015) and Gambetti and Musso (2017) apply the analysis to loans to the total private non-financial sector, while Hristov et al. (2012) investigate business loan supply shocks. Consequently, all these papers discard information on differences in the dynamics of business and household loans and cannot make a statement on potential differences in the transmission mechanisms to the real economy as well as on the relative importance of business versus household loan supply shocks in driving the business cycle. Duchi and Elbourne (2016) and Chiorazzo et al. (2017) actually investigate effects of credit supply shocks for both firms and households, but do so in separate VAR models. This impedes

[1] Although the terms "loan supply shocks" and "credit supply shocks" are often used interchangeably in the literature, there potentially can be a difference with respect to lending to businesses. Credit to firms in some papers is defined broader and includes debt securities like corporate bonds and commercial papers in addition to loans. For example, this is the case if data from the BIS database "Long series on total credit" are used.

a clean identification of sectoral loan supply shocks and neglects potentially important spillover effects between firms and households (Caggese and Pérez-Orive, 2016). Studying business and household loan supply shocks in one structural model allows gaining a better understanding of their macroeconomic effects and their historical contribution in shaping business cycles. Potential differences in their impact on the real economy are relevant for policymaking and financial regulation, as well as for designing financial frictions in theoretical models.

The paper contributes to the literature by providing the first structural time series analysis that isolates business and household loan supply shocks from each other in one model and assesses their macroeconomic effects. This distinction reveals some interesting differences in their macroeconomic effects and overall importance in driving business cycles. The main results of the analysis show that both loan supply shocks mainly operate through a quantitative channel, that is, they have a strong and prolonged effect on the corresponding loan volume, but almost none on the loan rate at the short horizon. The effect of both loan supply shocks on real GDP as well as on employment is similar in the first quarters after the shock impact, but household loan supply shocks are more persistent and thus have a larger cumulative effect. Household loan supply shocks appear to resemble classical demand shocks since they depress inflation, provoke an easing of monetary policy, and also affect business loans over time. Moreover, they exhibit a significantly negative impact on consumption and a marginally negative one on real house prices and investment. They also lead to a rise in the private saving rate at medium horizons. Business loan supply shocks, on the other hand, have a quite short-lived impact on investment and also marginal effects on consumption and net exports-to-GDP around one quarter after the shock has hit. They further slightly affect the volume of corporate bonds in the short term as firms with access to capital markets seem to be able to substitute loans with corporate bonds at least partly. Finally, forecast error variance decompositions and a historical decomposition reveal that both loan supply shocks have contributed significantly to business cycle dynamics over the sample period, especially during the Great Recession following the global financial crisis. Having said this, results from sensitivity analyses suggest that in case of household loan supply shocks it is the drop in home mortgages during the global financial crisis that seems to be a main driver behind these findings.

Overall, the study shows that household loans play a crucial role for the U.S. macroeconomy. This substantiates theoretical and empirical works alike that stress the importance of household deleveraging for the economy (Mian and Sufi, 2010b, 2011, Eggertsson and Krugman, 2012, Mian et al., 2013, Guerrieri and Lorenzoni, 2017, Mian et al., 2017, Jones et al., 2018). In particular, Mian et al. (2017) emphasize the predominant role of the household sector in materializing the real effects of positive credit supply shocks through consumption booms over firm debt driven investment booms. The boom-bust cycle in GDP induced by credit supply driven increases in household debt could be related to the decline in the private saving rate following phases of eased supply of household credit (Jappelli and Pagano, 1994). Indeed, my results are consistent with this view as they point to an effect of household loan supply shocks on private saving.

Regarding the debate whether a supply-driven mortgage boom contributed to the U.S. housing bubble prior to the last financial crisis (Milcheva, 2013, Favara and Imbs, 2015, Justiniano et al., 2015, 2017), my empirical framework points to a marginal and short-lived impact of household loan supply shocks on real house prices. Further, I also corroborate microeconometric findings on the impact of supply driven cutbacks of business loans on investment (Gan, 2007, Duchin et al., 2010, Gaiotti, 2013, Bucă and Vermeulen, 2017, Amiti and Weinstein, 2018) and corporate bonds (Adrian et al., 2012, Becker and Ivashina, 2014), although these effects turn out to be short-lived as well.

The empirical analysis of business and household loan supply shocks is accomplished by applying a structural vector autoregressive (SVAR) model for quarterly U.S. data over recent decades. The structural shocks are identified by combining sign and zero restrictions, using the recent algorithm by Arias et al. (2018) which is the only one drawing independently from the posterior distribution over the structural parameterization conditional on the restrictions. To better pin down the two loan supply shocks, I additionally impose some magnitude restrictions and further identify three conventional macroeconomic shocks, namely aggregate supply, aggregate demand and monetary policy shocks. All signs are imposed on impact only and are based upon a range of DSGE models (Atta-Mensah and Dib, 2008, Gilchrist et al., 2009, Christiano et al., 2010, Cúrdia and Woodford, 2010, Dib, 2010, Gerali et al., 2010, Brzoza-Brzezina and Makarski, 2011, Gertler and Karadi, 2011, Canova et al., 2015). Besides a baseline model consisting of seven variables, I estimate a couple of extended model versions in which I include an eighth variable to study the macroeconomic transmission mechanisms of the two loan supply shocks and further consider some sensitivity analyses.

The chapter proceeds as follows. The next section provides an overview of the related literature. Section 3.3 states some stylized facts about business and household loans and discusses potential differences in the effects of business and household loan supply shocks. Section 3.4 outlines the empirical framework and Section 3.5 reports and discusses the results as well as some sensitivity analyses. The last section concludes.

3.2 Related Literature

Research on credit markets has been on the agenda of macroeconomics for a long time and dates back to the seminal work of Fisher (1933). Bernanke and Gertler (1989) provided the first general equilibrium model in this respect, followed by influential contributions of Kiyotaki and Moore (1997), Bernanke et al. (1999) and Iacoviello (2005) among many others. However, these works and many building on them focus on the demand side of the credit market, based on the notion that financial markets in general are propagating and potentially amplifying shocks originating in other sectors. It is due to the events observed during the global financial crisis that have changed this view in the sense that credit markets are now perceived as potential sources of disturbances on their own.

To this end, several theoretical contributions in the field have extended the standard New Keynesian DSGE model by introducing an explicit financial sector. Important examples include Atta-Mensah and Dib (2008), Christiano et al. (2010), Cúrdia and Woodford (2010), Dib (2010), Gerali et al. (2010), Gertler and Kiyotaki (2010), Gertler and Karadi (2011), Brunnermeier and Sannikov (2014) and Canova et al. (2015). In these models, financial intermediaries drive a wedge between borrowers and lenders due to financial frictions. Typically, banks transmit financial shocks to the real sector of the economy by curtailing their supply of loans to firms who then have to cut back investment. Only a very few models, including Gerali et al. (2010), Brzoza-Brzezina and Makarski (2011) and Canova et al. (2015), incorporate lending to both firms and impatient households. This is interesting as supply-side cuts in lending to the household sector might induce deleveraging by households which has been shown to have substantial effects on the macroeconomy.[2] Moreover, Caggese and Pérez-Orive (2016) demonstrate that household deleveraging and credit shocks to firms interact and substantially amplify each other.

In addition to these theoretical contributions, numerous empirical studies have attempted to assess the macroeconomic relevance of loan supply shocks.[3] The key challenge in empirical works regards the question of how to isolate loan supply innovations as their exact identification comes along with several difficulties. First, supply disturbances have to be separated from demand-driven ones since this is crucial regarding policy implications. Further, one needs to ensure that variations in the supply of loans are the consequence of independent developments within the financial sector (that is, due to strategic decisions taken by financial intermediaries) and not an endogenous response to other changing macroeconomic conditions and disturbances (for example, due to monetary policy innovations).

Empirical macroeconomic studies attempt to identify and analyze loan supply shocks in structural VAR models using aggregate time series data. Researchers have employed a couple of different identification strategies. Some authors have used simple recursive identification schemes (Musso et al., 2011), partly in combination with credit mix variables to better distinguish credit supply from credit demand (Abildgren, 2012, Milcheva, 2013). Walentin (2014) analyzes the business cycle effects of shocks to a constructed mortgage spread measure included in recursively identified VAR models. Gilchrist and Zakrajšek (2012b) collect data on prices of individual corporate bonds traded in the secondary market and create the so-called "Excess Bond Premium" (EBP), which controls for movements in expected defaults. Shocks to the EBP have a substantial impact on economic activity and asset prices (Gilchrist and Zakrajšek, 2012a).[4] Another possibility to achieve identification is to proxy loan supply shocks by applying data from surveys mirroring lending conditions (prominent examples are the "Senior Loan Officer Opinion Survey

[2] See Eggertsson and Krugman (2012), Guerrieri and Lorenzoni (2017), and Jones et al. (2018) for theoretical contributions, and Mian and Sufi (2010a) and Mian et al. (2013) for empirical evidence.

[3] Early empirical contributions identifying loan supply shocks include Peek et al. (2003) and Driscoll (2004).

[4] In general, shocks to credit spread measures exhibit the same pattern as conventional credit supply shocks as they move the price and volume of credit in opposite directions. However, these measures do not identify a pure credit supply shock since they also reflect innovations in risk premia, which in turn manifest themselves in changing credit supply.

on Bank Lending Practices" (SLOOS) of the Fed and the ECB's "Bank Lending Survey" (BLS)). Lown and Morgan (2006) and Bassett et al. (2014) include such measures in recursively identified VAR models[5], whereas Altavilla et al. (2015) and Takahashi (2017) use such measures as an external instrument for identifying bank loan supply shocks.

Most papers rely on sign restrictions or a combination of sign and short-term exclusion restrictions to identify loan supply shocks. The rationale is based on the notion that loan supply shocks move the price (usually a composite lending rate or a credit spread measure) and the quantity of loans (the outstanding loan volume) in opposite directions, whereas a loan demand shock moves them in the same direction. This is supported by DSGE models that incorporate loan supply shocks. Furthermore, in a meta-study Mumtaz et al. (2018) show that identification by means of sign restrictions works well in recovering the underlying loan supply shock derived from a DSGE model. Contributions that apply sign restrictions to identify loan supply shocks include inter alia Hristov et al. (2012), Meeks (2012), Peersman (2012), Furlanetto et al. (forthcoming), as well as Barnett and Thomas (2014) and Duchi and Elbourne (2016) who combine sign and zero restrictions. Bijsterbosch and Falagiarda (2015) and Gambetti and Musso (2017) estimate time-varying parameter VAR models with stochastic volatility to analyze the changing business cycle effects of credit/loan supply shocks identified via sign restrictions. In addition, sign restrictions have also been applied to examine the international transmission of credit supply shocks by means of FAVAR models (Helbling et al., 2011) and global VAR models (Eickmeier and Ng, 2015, Fadejeva et al., 2015, Kick, 2016).

Besides these macroeconometric contributions, numerous researchers have used microeconomic data to explore the role played by loan supply for firms and households.[6] However, most of these works focus on disentangling loan supply from loan demand effects in response to specific events at one point in time and evaluate the relevance of supply effects on lending and other economic key figures. Furthermore, except Haltenhof et al. (2014) who compare the effects of access to bank loans for firms and households on employment in the manufacturing sector in one single model, most microeconometric works also study the impact of loan supply constraints separately either on firms or on households.

[5] There are some limitations in employing such indicators on bank lending standards as endogenous variables in recursively identified VAR models, the most severe being endogeneity concerns. Bassett et al. (2014) try to control for these endogeneity issues by purging their diffusion measure from a plethora of bank-individual and macroeconomic effects. Still, as Mumtaz et al. (2018) illustrate it is far from obvious if their proxy measure indeed identifies a loan supply shock and not a related shock.

[6] Examples of these microeconometric works include Cornett et al. (2011), Puri et al. (2011) and De Haan et al. (2017) (for looking at banks' reduction of loan supply in response to specific events), Gan (2007), Khwaja and Mian (2008), Ivashina and Scharfstein (2010), Duchin et al. (2010), Santos (2011), Jiménez et al. (2012), Gaiotti (2013), Kahle and Stulz (2013), Becker and Ivashina (2014), Chodorow-Reich (2014), Greenstone et al. (2014), Haltenhof et al. (2014), Iyer et al. (2014), Duygan-Bump et al. (2015), Bucă and Vermeulen (2017), Amiti and Weinstein (2018) and Bentolila et al. (2018) (for assessing the effects of loan supply constraints for firms), and Damar et al. (2014), Gropp et al. (2014), Haltenhof et al. (2014), Ramcharan et al. (2016), Di Maggio and Kermani (2017), Jensen and Johannesen (2017) and Mondragon (2018) (for studying implications of loan supply cut-backs to households). Some authors have utilized the aforementioned data of lending surveys to carry out microeconometric analyses (De Bondt et al., 2010, Hempell and Kok Sørensen, 2010, Blaes, 2011, Del Giovane et al., 2011).

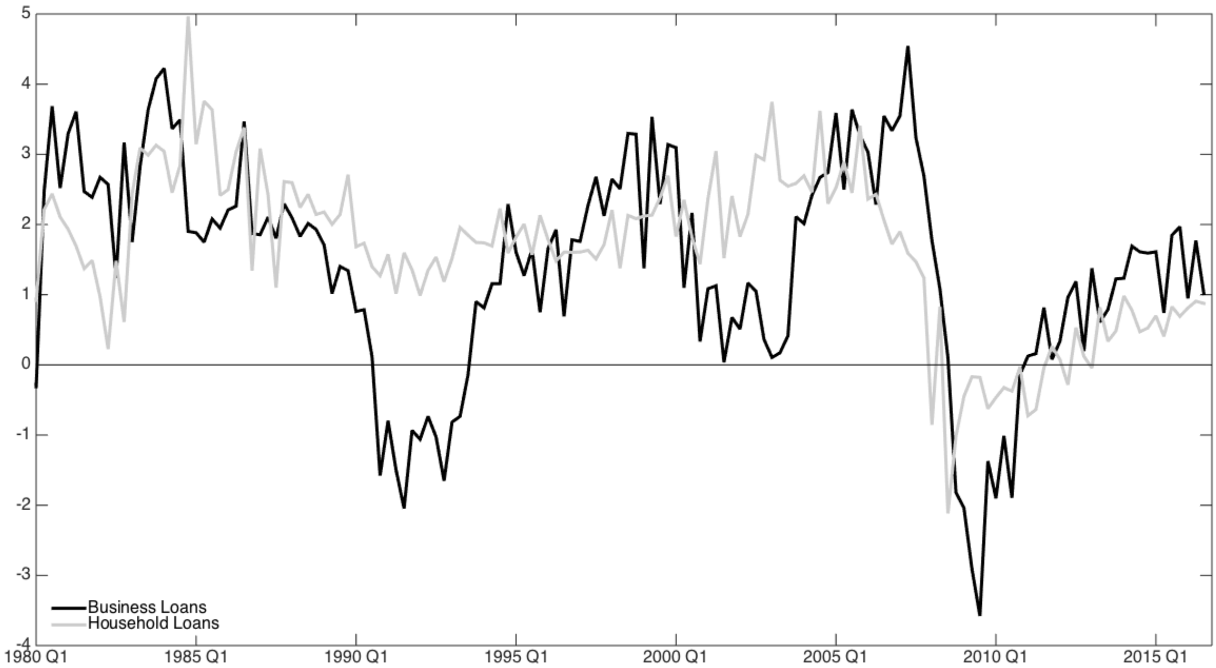
3.3 Business Loans versus Household Loans

This section starts by pointing out some stylized facts about business and household loans. After discussing factors underlying loan supply shocks, potential effects of and differences between business and household loan supply shocks with regards to the macroeconomy are compared.

3.3.1 Stylized Facts

Before turning to the empirical analysis it is useful to have a brief view on some stylized facts of business and household loans over the sample period of 1980Q1 to 2016Q4. Figure 3.1 depicts the seasonally adjusted nominal quarterly growth rate of the two loan aggregates over the sample period and Table 3.1 reports some descriptive statistics of the two series. The first fact to notice is that business loans are more volatile than household loans. Nominal growth of household loans has been positive in every quarter except the period encompassing the global financial crisis. The average quarterly growth is 1.65% (compared to 2.15% if the sample period ends in 2006Q4 to exclude the financial crisis) with a standard deviation of 1.14% (0.75%). In contrast, additionally to the global financial crisis quarterly growth of business loans turned also negative between 1991Q1 and 1993Q4 during the early 1990s recession. Moreover, growth rates were

Figure 3.1: Nominal Quarterly Growth Rates of Business and Household Loans



Note: The figure shows the seasonally adjusted nominal quarterly growth rates of business (black line) and household (gray line) loans over the sample period of 1980Q1 to 2016Q4. Business loans refer to the outstanding loan volume of non-financial businesses, household loans to the outstanding loan volume of households and nonprofit organizations. Data is obtained from the Flow of Funds Accounts of the United States; see Table 3.4 in Appendix 3.B for details.

Table 3.1: Stylized Facts of Business and Household Loans

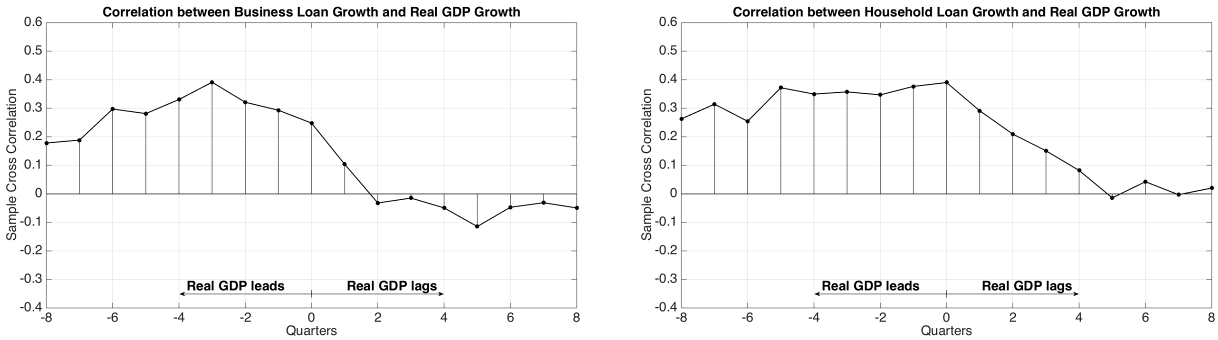
	Loans to Non-Financial Businesses	Loans to Households and NPOs
Average nominal quarterly growth	1.41%	1.65%
Standard deviation	1.56%	1.14%
Correlation to each other	0.52	0.52
Correlation to real GDP growth	0.25	0.39
Lead(-)/lag(+) w.r.t. real GDP	+3	0
Average share in total sector liabilities	35.03%	95.83%

Note: The table reports some stylized facts about business and household loans for the sample period of 1980Q1 to 2016Q4. Business loans refer to the outstanding loan volume of non-financial businesses, household loans to the outstanding loan volume of households and nonprofit organizations. Calculations are with respect to the seasonally adjusted nominal quarterly growth rate. Data is obtained from the Flow of Funds Accounts of the United States; see Table 3.4 in Appendix 3.B for details.

negative at the first quarter of the sample and close to zero in some quarters following the dot-com bubble between 2001 and 2003. Consequently, the average quarterly growth of business loans is smaller (1.41%/1.68%) and its standard deviation larger (1.56%/1.40%). The more cyclical behavior of business loans emerges even better if nominal annual growth rates are considered (see Figure 3.14 in Appendix 3.C). Accordingly, the correlation between the quarterly growth rates of the loan aggregates amounts to a modest 0.52. In order to get a first glance on linkages of the two loan aggregates to the business cycle, Table 3.1 also reports the correlation to real GDP growth and Figure 3.2 shows the cross-correlation between the quarterly growth rates of the loan volumes and real GDP growth. Interestingly, business loans have a smaller correlation with real GDP growth and lag it by three quarters, while household loans exhibit a somewhat higher correlation and are coincident with it.

Further, loans account for 95.83% of total liabilities of households, while they represent only 35.05% of total liabilities of non-financial businesses as U.S. corporate businesses fulfill a good

Figure 3.2: Correlation Between Loans Growth and Real GDP Growth



Note: The figure shows the sample cross-correlation between business (left panel) and household (right panel) loan growth and real GDP growth over the sample period of 1980Q1 to 2016Q4. Business loans refer to the outstanding loan volume of non-financial businesses, household loans to the outstanding loan volume of households and nonprofit organizations. Data is obtained from the Flow of Funds Accounts of the United States; see Table 3.4 in Appendix 3.B for details.

deal of their financing needs by market-based debt securities such as corporate bonds and commercial papers. This is also reflected in the fact that the share of household loans in total loans to the non-financial private sector is larger and has become more important over the sample period from approximately 57% of total loans at the beginning of the sample to almost 70% in 2004 (see Figure 3.13 in Appendix 3.C). Finally, it is important to note that home mortgages constitute the majority of the outstanding household loan volume, with on average 70.47% of total loans to households over the sample period.

These stylized facts reveal that the dynamics of business and household loans differ significantly and underscore the necessity to differentiate between them as mixing them together into one aggregate loan measure for the whole private sector potentially masks important information. On the other hand, just focusing on one sector likely does not reveal the whole effect of loan supply disturbances on the macroeconomy.

3.3.2 Motivating Two Separate Loan Supply Shocks

Different dynamics of business and household loans are the result of both, demand and supply factors. Especially since the global financial crisis there is an ongoing debate on the predominant mechanisms causing the sharp decline in lending and economic activity during the Great Recession.[7] Despite the importance of demand shocks, a leading account shared by many is that financial shocks, particularly loan supply shocks, play a crucial role as well. In the face of loan portfolio losses and dropping asset values, cutting back lending to the private non-financial sector is a possible way for banks to scale down their asset holdings and to deleverage. Macroeconomic studies report a considerable and persistent effect of loan supply shocks on the loan volume as well as a non-negligible although more short-lived effect on real GDP (see Hristov et al., 2012, Barnett and Thomas, 2014, Bijsterbosch and Falagiarda, 2015, Duchi and Elbourne, 2016, and Gambetti and Musso, 2017, among others). Hence, while there is evidence on the relevance of loan supply shocks, a distinction between business and household loan supply shocks in one model in order to reveal potential differences in their macroeconomic effects is missing.[8]

[7] In this respect, Kahle and Stulz (2013) discuss different theories, albeit with a focus on corporate lending during the recent financial crisis. Note that according to the view that demand shocks are the main driver of lending, there is no causal link going from reduced lending to a decline in output. Rather, firms cut back on investment and households reduce consumption in the wake of heightened uncertainty about future economic developments. In addition, worsening business prospects and decreasing asset values exert downward pressure on a firm's net worth and lead to a fall in their available collateral against which they can borrow; the well-known financial accelerator mechanism. As for many households their house is the main asset, the financial accelerator mechanism is in place for households, too (Mian and Sufi, 2011, Mian et al., 2013).

[8] To the best of my knowledge, only Haltenhof et al. (2014) compare the impact of loan supply reductions towards businesses and households on the real economy in one single model. They find that households' access to bank loans matters more for employment in the manufacturing sector. However, they do not employ a macroeconometric time series model. In contrast, other microeconometric papers that distinguish between firms and households by utilizing data of the ECB's BLS perform the analysis in separate panel regressions for the two sectors (see De Bondt et al., 2010, Hempell and Kok Sørensen, 2010 and Del Giovane et al., 2011). Regarding macroeconometric studies, Duchi and Elbourne (2016) and Chiorazzo et al. (2017) also estimate two separate VAR models in their assessment of credit supply shocks to firms and households.

First, note that the concept and triggering events underlying business and household loan supply shocks are the same. In the most general sense, a loan supply shock can be thought of as a time-varying friction between borrowers and lenders, which is characterized by an exogenous change in the supply of loans by financial intermediaries to the private non-financial sector. The supply of loans can be altered by simply expanding/reducing the amount made available, by increasing/decreasing the price of the loan, that is, the loan rate, and/or by modifying non-price lending standards (that is, the terms of the lending contract such as collateral requirements, additional charges, etc.). The defining feature of a loan supply shock is that it is an independent innovation originating within the financial sector that is exogenous to other macroeconomic disturbances. Endogenous reactions by financial intermediaries as a response to changing macroeconomic conditions (for example, a change in the monetary policy stance) are hence not considered as loan supply shocks. Put differently, loan supply shocks lead to supply-side changes in lending which cannot be explained by underlying macroeconomic fundamentals. Events triggering such exogenous shifts in loan supply are manifold (Gambetti and Musso, 2017). Given the last financial crisis, the most natural example are sudden changes in the value of assets held by banks, or changes in the ability of banks to raise capital. Further, one can think of changes in bank capital (for example due to modified regulatory capital ratio requirements), alterations in the pricing of default risk by banks, or changing degrees of competition in the banking sector. In any case, all these events may transmit to the real sector via adjustments in the lending behavior of intermediaries.

Related empirical works suggests that banks strategically discriminate between business and household loans along several dimensions when facing one of these events. De Haan et al. (2017) find that corporate lending growth and loan rates are more sensitive to wholesale funding shocks than the corresponding household ones. As corporate loans have on average a shorter maturity and higher risk profile, banks can more easily adjust their asset side, both in terms of size and risk, by altering their corporate loan portfolio. Calcagnini and Giombini (2009) report that Italian banks efficiently screen and monitor firms before approving a loan, whereas in case of households and sole proprietorships they tend to neglect screening and monitoring procedures and replace them with personal guarantees. Both findings imply that banks are more sensitive with respect to business loans when facing some of the events described above.[9]

However, firms are also more likely to compensate for reduced loan supply since they can substitute loans with other sources of finance such as issuing bonds or equity on the capital market or through internal funds and cash holdings. Indeed, Becker and Ivashina (2014) provide evidence of corporates substituting bank loans with bonds at times characterized by bank loan supply contractions and tight lending standards. Leary (2009) reports that during bank lending

[9] Moreover, as will be described below, the data used for the loan volume captures not only loans by banks but generally by all kinds of financial intermediaries. This includes intermediaries which concentrate on lending to one sector like, for example, credit unions which are serving mainly households. If these lenders are faced with liquidity constraints or changing regulatory requirements this naturally affects lending just to this sector. See Ramcharan et al. (2016) for a microeconometric paper making use of a broad dataset on credit unions.

contractions bank-dependent firms shift towards equity, while non-bank dependent firms raise increasingly capital on public debt markets. Furthermore, there is evidence that firms draw on their existing credit lines during financial turmoil periods (Campello et al., 2010, Ivashina and Scharfstein, 2010). From a theoretical perspective, De Fiore and Uhlig (2015) present a DSGE model with endogenous corporate debt structure and illustrate how the ability of firms to substitute among alternative instruments of external finance attenuates the macroeconomic repercussions of financial sector distress. Having said this, especially small firms without access to the bond market and firms that have been relying on relationship banking might find it difficult and expansive to compensate for the fall in the supply of bank loans with other forms of debt financing (Adrian et al., 2012). Moreover, during a severe crisis distress might not be confined to the intermediary sector, but affect the capital market (that is, bond and stock markets) as well, making other forms of debt financing expansive (Gorton, 2009, Adrian et al., 2012). Still, in contrast to firms the ability of households to substitute loans is more limited as they basically can only draw down liquid assets to smooth consumption (Damar et al., 2014).

Given these considerations, the ultimate impact of the two loan supply shocks on the macroeconomy is a priori indeterminate, but the channels through which they affect economic activity likely differ. Business loan supply shocks can be assumed to primarily have an effect on real economic activity via investment, while household loan supply shocks transmit to the real economy via influencing private consumption as well as residential investment. Related works also motivate investigating their impact on net exports and private saving. Regarding the former, Bahadir and Gumus (2016) find that in emerging market economies household credit is more related to trade deficits than business credit, while Jappelli and Pagano (1994) reveal that eased access to credit for households negatively affects private saving.

Finally, differences in the transmission channels could also lead to a different response of prices to the two loan supply shocks. An adverse business loan supply shock that depresses investment and decreases aggregate demand might also lower inflation, but at the same time absent investments could inhibit technological efficiency and the production process, leading to higher marginal costs and in turn to higher prices. Likewise, loans itself could be seen as an input to the production process, implying that higher loan rates increase costs which could feed through to prices. Thus, while in case of firms it is ultimately an empirical question whether the demand or the supply channel dominates, an adverse household loan supply shock can be expected to curb inflationary pressure through reduced consumption demand. In addition, as mortgages represent the largest share of the outstanding volume of household loans, household loan supply shocks can further be expected to affect house prices. There is evidence that the large expansion of mortgages has contributed to the boom in U.S. house prices prior to the last financial crisis (Milcheva, 2013, Favara and Imbs, 2015, Justiniano et al., 2015).

The next section presents the structural VAR model and the identification scheme applied to identify the two loan supply shocks and to study their effects and differences in them on loan volumes and rates as well as on a range of macroeconomic and financial variables (namely, real GDP, inflation, federal funds rate, investment, consumption, net exports, employment, real house prices, corporate bonds, and private saving).

3.4 The Empirical Approach

This section starts by briefly outlining the specification and estimation of the structural VAR model and describes the data. Subsequently, I discuss the proposed identification scheme.

3.4.1 SVAR with Sign and Zero Restrictions

The analysis of the two loan supply shocks is performed by estimating a conventional structural VAR model as in Rubio-Ramírez et al. (2010):

$$\mathbf{y}_t'\mathbf{A}_0 = \sum_{\ell=1}^{p} \mathbf{y}_{t-\ell}'\mathbf{A}_\ell + \mathbf{c} + \boldsymbol{\epsilon}_t' \qquad \text{for } 1 \leq t \leq T, \tag{3.1}$$

where $\mathbf{y}_t$ is an $n \times 1$ vector of endogenous variables, $\mathbf{A}_\ell$ represents an $n \times n$ matrix of parameters for $0 \leq \ell \leq p$ with $\mathbf{A}_0$ invertible, $\mathbf{c}$ is a $1 \times n$ vector of parameters, $\boldsymbol{\epsilon}_t$ is an $n \times 1$ vector of exogenous structural shocks, p denotes the lag length and T the sample size. The vector of structural shocks $\boldsymbol{\epsilon}_t$ is Gaussian with mean zero and identity covariance matrix, that is, $\mathbb{E}[\boldsymbol{\epsilon}_t\boldsymbol{\epsilon}_t' \mid \mathbf{y}_0, \ldots, \mathbf{y}_{1-p}] = \boldsymbol{\Sigma}_{\boldsymbol{\epsilon}} = \mathbf{I}_n$. Defining the $m \times n$ matrix $\mathbf{A}_+' = [\mathbf{A}_1' \ \cdots \ \mathbf{A}_p' \ \ \mathbf{c}']$, where $m = np + 1$, and $\mathbf{x}_t' = [\mathbf{y}_{t-1}' \ \cdots \ \mathbf{y}_{t-p}' \ \ 1]$ for $1 \leq t \leq T$ allows rewriting Equation (3.1) as

$$\mathbf{y}_t'\mathbf{A}_0 = \mathbf{x}_t'\mathbf{A}_+ + \boldsymbol{\epsilon}_t' \qquad \text{for } 1 \leq t \leq T. \tag{3.2}$$

The reduced-form representation of the structural VAR model given in Equation (3.2) is

$$\mathbf{y}_t' = \mathbf{x}_t'\mathbf{B} + \mathbf{u}_t' \qquad \text{for } 1 \leq t \leq T, \tag{3.3}$$

where $\mathbf{B} = \mathbf{A}_+\mathbf{A}_0^{-1}$, $\mathbf{u}_t' = \boldsymbol{\epsilon}_t'\mathbf{A}_0^{-1}$, and $\mathbb{E}[\mathbf{u}_t\mathbf{u}_t'] = \boldsymbol{\Sigma} = (\mathbf{A}_0\mathbf{A}_0')^{-1}$. Hence, the matrices $\mathbf{B}$ and $\boldsymbol{\Sigma}$ are the reduced-form parameters, while $\mathbf{A}_0$ and $\mathbf{A}_+$ are the structural parameters.

As is well known, identification of structural shocks requires to impose at least $n(n-1)/2$ restrictions on the impact matrix $\mathbf{A}_0^{-1}$. For this purpose, I apply a combination of sign and zero restrictions to identify the structural shocks of interest using the algorithm of Arias et al. (2018).[10] Additionally, I implement magnitude restrictions which are not required for identification, but

[10] Recent advances in structural time series analysis have yielded efficient algorithms for combining sign and short-run exclusion restrictions in identifying structural shocks. Mountford and Uhlig (2009) propose a penalty function approach, but Arias et al. (2018) demonstrate that their method entails imposing implicit restrictions on variables thought to be unrestricted. Alternatively, block recursive models have been identified by utilizing subrotations that preserve the imposed zero restrictions when draws for the rotation matrix are generated (Baumeister and Benati, 2013, Benati, 2013, and Benati and Lubik, 2014). As these methods are limited to block recursive models, a more flexible algorithm has been proposed by Binning (2013). However, only Arias et al. (2018) show that their algorithm independently draws from the posterior distribution over the structural parameterization conditional on the imposed sign and zero restrictions.

help to better pin the two loan supply shocks. In a nutshell, the proposed importance sampler algorithm of Arias et al. (2018) works as follows:

1. Draw $(\mathbf{B}, \mathbf{\Sigma})$ independently from a normal-inverse-Wishart distribution.
2. Define an orthogonal matrix $\mathbf{Q}$ that incorporates the zero restrictions in the orthogonal reduced-form parameterization, conditional on the reduced-form parameters $(\mathbf{B}, \mathbf{\Sigma})$.
3. Transform the orthogonal reduced-form parameterization $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ into the structural parameterization $(\mathbf{A}_0, \mathbf{A}_+)$.
4. If $(\mathbf{A}_0, \mathbf{A}_+)$ satisfies the sign and magnitude restrictions, then calculate its importance weight. Otherwise, set its importance weight to zero.
5. Return to Step 1 until the required number of draws has been obtained.
6. Re-sample with replacement using the importance weights.

A detailed technical description of the algorithm is provided in Appendix 3.A. The results shown below are based on an effective sample size of 1000 independent draws satisfying the sign, magnitude, and zero restrictions in case of the baseline model and 500 draws in case of the extended model versions. As the identification approach results only in a set of admissible model estimates, I present commonly used posterior median estimates together with the corresponding 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution. Note that using Bayesian methods accounts for uncertainty in the parameters, but that the probability band reflects both this uncertainty as well as the distribution across models which is not related to sampling uncertainty (Fry and Pagan, 2011). Moreover, one has to be aware that the posterior median responses stem from different models (Fry and Pagan, 2011). This is particularly problematic when calculating forecast error variance decompositions and historical decompositions. Therefore, I report for these two structural analysis tools in addition results based on the Median Target model as proposed by Fry and Pagan (2011), derived from taking into account the impact and the first year afterwards.[11]

3.4.2 Data

The baseline model includes seven variables for the United States at quarterly frequency spanning the time period from 1980Q1 to 2016Q4. These are real GDP, the consumer price index, the federal funds rate mirroring the monetary policy stance, nominal loan volumes for both, the non-financial business and the household sector, as well as sector-specific composite loan rates. In a couple of extended model versions I add an eighth variable to the system, namely, in turn, real

[11] Inoue and Kilian (2013) point out that the median is not a valid measure of central tendency. Hence, ideally one would like to implement their proposed method and calculate the posterior mode of the joint impulse response distribution of all admissible models. However, their method is computationally cumbersome in case of partially identified models as one needs to calculate the marginal impulse response distribution by integrating out the response to unidentified shocks.

investment, real personal consumption expenditures, net exports, employment, real house prices, outstanding corporate bonds, and net private saving. Most variables enter the system in first log-differences, that is, quarterly growth rates. Exceptions are net exports and net private saving which are expressed in percent to nominal GDP as well as the three interest rates. Appendix 3.B provides detailed information on data sources, exact definitions of the variables and their treatment.

The choice of the concrete measure for the loan volume and the lending rate has non-negligible influence on the effects of loan supply shocks. I use data from the Flow of Funds Accounts of the United States on loans to the non-financial business sector and the household sector, which are corrected for loan sales and securitization.[12] In reference to the empirical analysis two points need to be kept in mind. First, the focus of the analysis lies on loans taken out with financial intermediaries as opposed to other forms of market-based credit and debt securities such as corporate bonds and commercial papers.[13] This choice is motivated by evidence of a substitution effect between loans and bonds (Adrian et al., 2012, Becker and Ivashina, 2014), which I investigate in one of the extended model versions. Second, these loan volume measures do not only comprise loans originated by banks, but also other financial intermediaries. This is important in case of the United States, where loans granted by commercial banks account for a comparatively small fraction of total loans. For example, with respect to households this measure includes loans by credit unions and mortgages provided by government-sponsored enterprises. In a sensitivity analysis, I report how results change when only commercial and industrial loans from all commercial banks in case of businesses and consumer loans from all commercial banks in case of households are considered.

Regarding the price of loans, I apply a sector-specific composite lending rate. This follows Gambetti and Musso (2017), but has the advantage that the aggregation level is lower. Some authors instead apply credit spread measures to mirror the price of loans/credit, or more generally of credit conditions. On the one hand, this in principle allows to capture not only loan supply conditions that manifest itself via changes in loan rates, but potentially also those that work via non-price channels and are due to changes in the risk-bearing capacity of financial intermediaries (Duchi and Elbourne, 2016). For example, varying risk-taking appetite might lead financial intermediaries to control their supply of loans via non-price lending standards such as non-interest charges or collateral requirements (van der Veer and Hoeberichts, 2016). On the other hand, credit spreads also move due to changing default risk of borrowers which might be inter alia affected by aggregate demand shocks (Hristov et al., 2012); something that is inherently different from the underlying idea of a loan supply shock. Furthermore, using credit spread

[12] As Gambetti and Musso (2017) emphasize this correction is important to gauge properly the amount of loans originated by banks, as in recent years the fraction of loans granted and subsequently securitized and taken off banks' balance sheets has been significant.

[13] For instance, Bijsterbosch and Falagiarda (2015) and Eickmeier and Ng (2015) use "credit to the non-financial private sector by all lending sectors" provided by the BIS which includes not only loans, but also debt securities. Hence, their credit supply shocks represent shocks to the general supply of external finance.

measures raises the question whether one general spread for identifying both loan supply shocks should be used or if sector-specific spreads should be considered (Duchi and Elbourne, 2016). Taken together, in favor of a clean identification of loan supply shocks I therefore prefer pure lone rates to credit spread measures.

3.4.3 Identification Scheme

The main challenge in identifying loan supply shocks in empirical macroeconomic models using aggregate time series data lies in disentangling them from loan demand shocks. While events triggering a loan supply shock are different from those related to a loan demand shock, their effects on the macroeconomy are quite similar. This paper follows the most common approach in the literature to isolate loan supply shocks and applies sign restrictions. First, as Mumtaz et al. (2018) show, identification via sign restrictions (particularly in combination with quantity restriction on the forecast error variance) works comparatively well in recovering the underlying loan supply shock of a DSGE model. Second, combining sign restrictions with zero restrictions provides a simple way of additionally distinguishing business and household loan supply shocks.[14] All sign and zero restrictions are just imposed on impact and are supported by a range of DSGE models. In particular, DSGE models that explicitly model a financial/banking sector and consider events associated with loan supply shocks include Atta-Mensah and Dib (2008), Gilchrist et al. (2009), Christiano et al. (2010), Cúrdia and Woodford (2010), Dib (2010), Gertler and Karadi (2011) as well as Gerali et al. (2010), Brzoza-Brzezina and Makarski (2011) and Canova et al. (2015), with the latter three incorporating separate lending to both sectors and distinguishing between loan supply shocks affecting firms from those affecting households. The complete identification scheme of the baseline model as well as of all extended model versions is given in Table 3.2.

Looking at this set of theoretical models reveals that the response of three variables to loan supply shocks is consistent across all models: an adverse loan supply shock leads to a decrease in real GDP and the loan volume on impact, while the lending rate increases on impact. This result also holds true separately for the two loan supply shocks at the disaggregated sectoral level. The opposite movement of loan volume and corresponding loan rate represents the distinct feature of loan supply shocks and distinguishes them from loan demand shocks which drive these two variables in the same direction. The instantaneous response of real GDP seems plausible, in particular at a quarterly frequency, as in the aggregate it can be expected that firms reduce their investment expenditures and households their consumption expenditures, respectively, in response to an adverse loan supply shock. In order to avoid the implausible result that a loan supply shock has quantitatively a larger impact on real GDP than on the loan volume, I follow Eickmeier and Ng (2015) and Fadejeva et al. (2015) in additionally setting a magnitude restriction which ensures that only loan supply shocks are accepted whose contemporaneous impact on the

[14] In comparison, recursive identification schemes with proxy measures mirroring loan supply as well as identification through heteroskedasticity perform quite poorly, while identification by means of an external instrument works quite well, too (Mumtaz et al., 2018). However, additionally distinguishing business and household loan supply shocks seems tricky when applying any other identification method.

Table 3.2: Identification Scheme

Shock / Response	Business Loan Supply	Household Loan Supply	Aggregate Supply	Aggregate Demand	Monetary Policy
Real GDP	−	−	−	−, <Loan Vol.	−
Inflation Rate	0	0	+	−	−
Fed Funds Rate	∗	∗	∗	−	+
Loan Vol. NFBs	−, <RGDP	0	∗	∗	∗
Rate NFBs	+	0	∗	∗	∗
Loan Vol. HHs	0	−, <RGDP	∗	∗	∗
Rate HHs	0	+	∗	∗	∗
Resp. 8th variable:					
Investment	∗	∗	∗	∗	∗
Consumption	∗	∗	∗	∗	∗
Net Exports	∗	∗	∗	∗	∗
Employment	0	0	∗	∗	∗
House Prices	0	0	∗	∗	∗
Corporate Bonds	0	0	∗	∗	∗
Private Saving	∗	∗	∗	∗	∗

Note: The table shows the restrictions on the response of variables to the five identified shocks. The baseline model includes seven variables, while the extended model versions consist of eight variables. All restrictions are just imposed on impact and are consistent with theoretical models. An asterisk (∗) indicates that the response is left unrestricted. The estimation procedure ensures that the remaining two (three in the extended model versions) shocks which are left unidentified are different from the identified shocks with respect to their sign patterns on impact. For definitions of variables see Table 3.4 in Appendix 3.B.

loan volume is larger than on real GDP in absolute terms. This condition is supported by the DSGE models named above and helps to better isolate the two loan supply shocks, preventing that they absorb any other shocks for which the system does not control.

While the response of these three variables to loan supply shocks is robust across DSGE models, the response of the inflation rate and the monetary policy rate depends on modeling choices. Consequently, there is also no clear consensus in the empirical literature. Any sign restriction on these two variables is debatable, while leaving both unrestricted worsens the identification of the loan supply shock. I therefore place a contemporaneous zero restriction on inflation, while I leave the monetary policy response unrestricted. This choice is motivated by the common assumption of short-term price stickiness due to nominal rigidities (Halvorsen and Jacobsen, 2014).[15] Leaving the response of the policy rate unrestricted implies that the central bank is in principle allowed to react to a loan supply shock within the same quarter.

Finally, in order to separate business and household loan supply shocks, I assume that the two loan supply shocks have no contemporaneous effect on the loan volume and loan rate of the other sector. Hence, spillover effects from one loan supply shock to the loan volume and loan rate of the other sector are allowed to occur only one quarter after the shock has hit. This restriction is not only the most intuitive way to disentangle the two loan supply shocks, but is also largely

[15] Exploiting over-identifying restrictions, Lanne and Lütkepohl (2008) find statistical evidence for a zero restriction on inflation (strictly speaking, the implicit GDP deflator) in response to a monetary policy shock in the U.S., while output shows a small response on impact. It seems plausible that the same applies to loan supply shocks as well, thus supporting the proposed identification scheme.

supported by DSGE models that incorporate both shocks and find only limited sectoral spillover effects on impact (Gerali et al., 2010, Brzoza-Brzezina and Makarski, 2011, Canova et al., 2015). Taken all together, an adverse business/household loan supply shock has a negative effect on real GDP and the corresponding loan volume with the latter effect being larger on impact, a positive effect on the corresponding loan rate, and no contemporaneous effect on the inflation rate as well as the loan volume and the loan rate associated with the other sector.

In addition to the baseline model, I estimate several extended model versions with an eighth variable included in the system in order to obtain a more detailed look on the effects and transmission mechanisms of the two loan supply shocks. With regard to the respective eighth variable I refrain from placing any sign restriction on their response and either let them unrestricted (investment, consumption, net exports, private saving rate) or put an instantaneous zero restriction on their response when this seems justifiable (employment, house prices, corporate bonds).[16]

Besides the two loan supply shocks, I identify three standard macroeconomic shocks: an aggregate supply shock, an aggregate demand shock, and a monetary policy shock. Identification of these shocks follows conventional wisdom in the literature on business cycles and is supported by numerous theoretical models. I neither impose a restriction on the response of the loan volumes and loan rates, nor on any of the variables of the extended model versions.[17] The remaining two (three in the extended model versions) reduced-form shocks are left unidentified and are supposed to capture any disturbances not explained by the structural model.[18]

3.5 Macroeconomic Effects of Loan Supply Shocks

This section presents and discusses the empirical results of the study. First, impulse responses of the two loan supply shocks in the baseline model are shown and compared. This is followed by investigating the importance of the two shocks in explaining the forecast error variance of the endogenous variables, as well as their contribution to the historical evolvement of real GDP growth. The second subsection investigates the reaction of various macroeconomic key figures added as an eighth variable to the baseline model in response to the two loan supply shocks, while the last subsection summarizes results of some sensitivity analyses of the baseline model.

[16] Employment and house prices are slow-moving economic indicators, motivating a lagged response of these variables. In case of corporate bonds, the instantaneous zero restriction relies on the observation that issuing them involves several decision and implementation steps.

[17] Regarding the aggregate demand shock, I place a magnitude restriction that ensures a larger contemporaneous response of real GDP than of both loan volumes to exclude confounding them with loan demand shocks. Further, it might seem intuitive to place a negative sign restriction on the loan rates. However, as Hristov et al. (2012) discuss, in case of a substantial *negative* aggregate demand shock as experienced during the Great Recession, banks might actually react by *raising* loan rates as they are confronted with riskier borrowers because of deteriorating balance sheets, reduced collateral values, and worsened business prospects.

[18] I explicitly control in the algorithm that the unidentified shocks are different from the identified shocks with respect to their sign patterns on impact.

3.5.1 Results of the Baseline Model

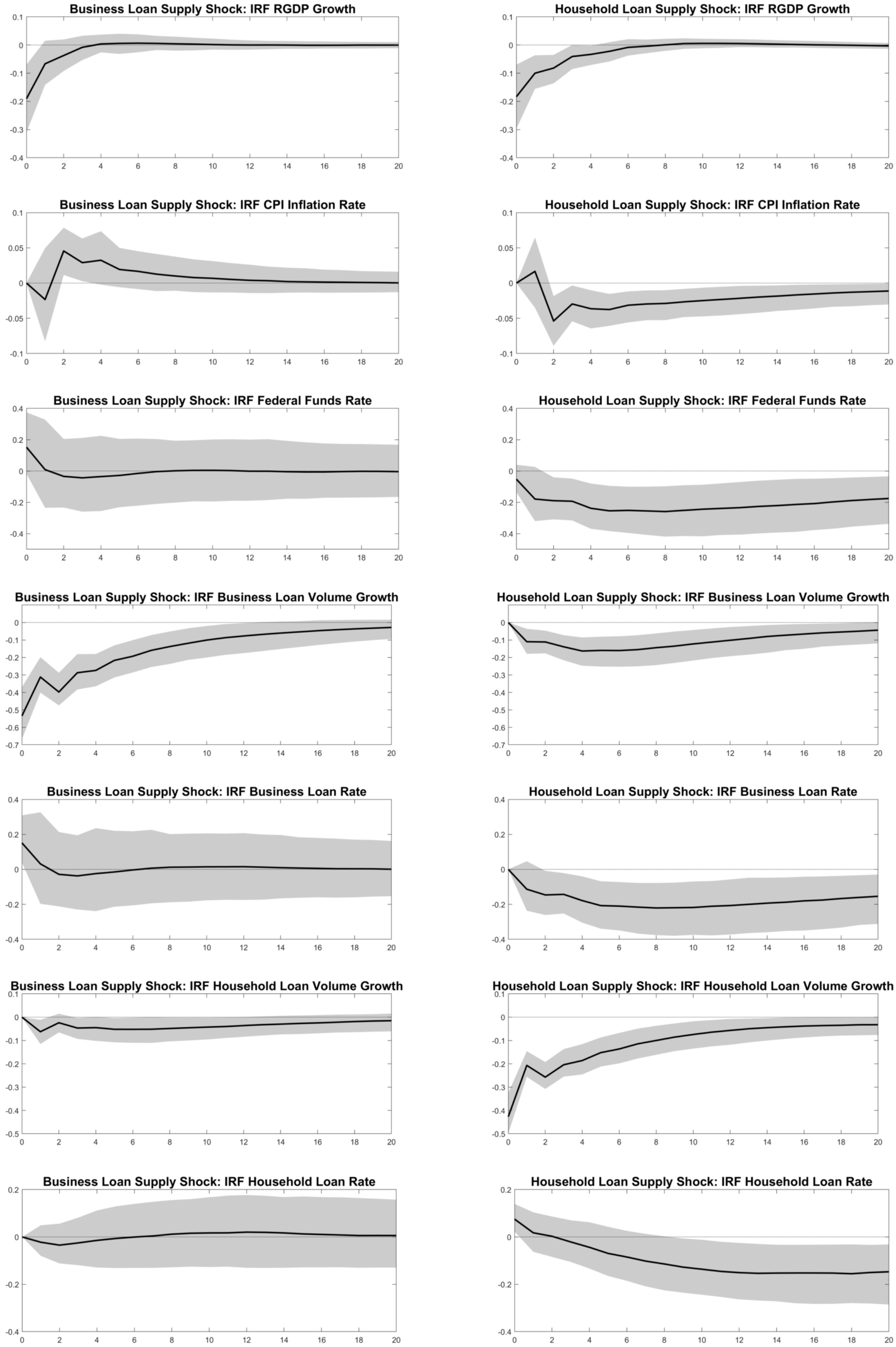
Impulse Response Analysis Figure 3.3 shows the impulse response of the variables in the baseline model to a negative, one-standard-deviation business and household loan supply shock, respectively. Impulse responses to the other identified shocks (aggregate supply, aggregate demand, and monetary policy) are provided in Appendix 3.C. For each variable the posterior median impulse response and the 68% point-wise probability band between the 16th and 84th percentile of the posterior distribution is depicted.

The characterizing feature of a loan supply shock is the opposing effect on the corresponding loan volume and loan rate. An adverse business loan supply shock lowers the growth rate of business loans by around 0.5 percentage points on impact and has a persistent effect on the business loan volume. The response of the business loan rate is only positive on impact and becomes indeterminate immediately afterwards. Similarly, an adverse household loan supply shock has a persistently negative effect on the growth rate of household loans, while the positive impact on the household loan rate turns negative and stays so until the end of the horizon. Thus, the results suggest that both loan supply shocks mainly operate through a quantitative channel by affecting the corresponding loan volume, while loan rates are only mildly affected on impact and in case of an adverse household loan supply shock even turn persistently negative afterwards. The long-lasting effect of loan supply shocks on the loan volume is a common finding in the literature, as is the rather short-lived and sometimes rebounding effect on lending rates (Hristov et al., 2012, Bijsterbosch and Falagiarda, 2015, Gambetti and Musso, 2017). In contrast, credit spreads seem to react stronger to loan supply shocks than pure lending rates (Barnett and Thomas, 2014, Duchi and Elbourne, 2016), presumably because they also capture non-price factors.

Real GDP growth weakens a bit more than 0.15 percentage points on impact after adverse business and household loan supply shocks. In case of a household loan supply shock, the whole 68% probability band of the posterior distribution remains below zero for almost five quarters, while the response of real GDP growth to a business loan supply shock turns indeterminate after the first quarter. Given that both shocks lead to a persistent decrease in the corresponding loan volume, this might imply that firms can at least partly substitute loans with other sources of finance and avoid long-run reductions in investment; an issue analyzed in more detail below.

Interestingly, the two loan supply shocks further differ with respect to the response of the inflation rate. There is a negative and persistent deflationary response starting two quarters after an adverse household loan supply shock has hit. In contrast, in case of an adverse business loan supply shock the posterior median response turns positive two quarters after the impact and remains so for at least two quarters. The deflationary effect after an adverse household loan supply might be due to reduced consumer demand, whereas increasing financing costs might prompt firms to raise prices following an adverse business loan supply shock. Similarly, there is a difference between the two shocks with respect to the federal funds rate that mirrors monetary policy as it is virtually unaffected by a business loan supply shock except on impact, while

Figure 3.3: Impulse Responses to Loan Supply Shocks



Note: The figure shows the posterior median impulse response of the seven variables in the baseline model to a negative, one-standard-deviation business loan supply shock (left column) and a negative, one-standard-deviation household loan supply shock (right column). Shaded areas represent 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution of 1000 draws that fulfill the restrictions. Vertical axes are in percentage points, horizontal axes are in quarters. See Table 3.4 in Appendix 3.B for definitions of variables.

the central bank reacts with a persistent easing of monetary policy in response to an adverse household loan supply shock.

Looking at the response of the loan volume and loan rate of the other sector reveals some further differences. While business loan volume and rate decrease persistently in response to an adverse household loan supply shock, the household loan volume decreases only marginally after an adverse business loan supply shock and the household loan rate is virtually unaffected by it. In conjunction with the persistent decrease in real GDP growth, a possible hypothesis would be that the curtailed supply of loans to households depresses aggregate demand and induces firms to reduce their investments and hence their demand for loans given gloomy economic prospects. In turn, intermediaries might then lower the lending rate to firms, in line with the decreasing federal funds rate.[19]

Summarizing, both loan supply shocks mainly operate through a quantitative channel, that is, they have a strong and persistent effect on the growth rate of the corresponding loan volumes, but almost no one on the loan rates on impact. Despite a quantitatively similar effect on real GDP growth on impact, effects of household loan supply shocks are longer-lasting and thus cumulatively larger. In general, household loan supply shocks seem to resemble classical demand shocks as they drive output and the price level in the same direction, which subsequently leads to a persistent reaction of the monetary policy rate. These results are consistent with findings from Mian et al. (2017) who emphasize the predominant role of the household sector in materializing the real effects of positive credit supply shocks through consumption booms over firm-debt driven investment booms. Furthermore, the more severe consequences of household loan supply shocks might be also related to the high leverage of the U.S. household sector, especially prior to the global financial crisis (Mian and Sufi, 2010a). Using Dutch data, Duchi and Elbourne (2016) also find that households are hit harder by credit supply shocks and suggest that the highly leveraged balance sheet of Dutch households might be one of the underlying reasons.

Finally, it is worth to briefly point out the effects of the other three macroeconomic shocks on the loan volumes and loans rates (see Figures 3.15 to 3.17 in Appendix 3.C). Remember that no restriction has been imposed on these variables in response to the macroeconomic shocks. The aggregate supply shock has no clear effect neither on the two loan volumes nor on the loan rates. An adverse aggregate demand shock has a persistently negative and quantitatively strong effect on both loan rates and further causes a slight decrease in business loan volume growth, while the household loan volume is unaffected. Surprisingly, the monetary policy shock does not affect any loan volume and the household loan rate and only has a marginally positive effect on the business loan rate until the first quarter after the shock impact. However, the impact of the monetary policy shock on the federal funds rate itself is quite weak.

[19] Having said this, note that it is impossible to determine whether really a demand-driven mechanism is at work, or if supply factors also play a role (that is, whether financial intermediaries themselves cut back the supply of business loans after an adverse household loan supply shock).

Forecast Error Variance Decomposition In oder to assess the quantitative importance of the two loan supply shocks for the business cycle in comparison to the three conventional macroeconomic shocks, Table 3.3 provides the forecast error variance decomposition of the variables in the baseline model. Specifically, I report the median share and the corresponding 68% probability band of all five identified shocks in explaining the forecast error variance of all variables on impact as well as at the 1- and 5-year forecast horizon. As the median share is not associated with a single model and consequently the explained shares by all shocks do not sum to one (Fry and Pagan, 2011), I additionally report the forecast error variance shares of the Median Target model for comparison in Table 3.5 in Appendix 3.C.

Both loan supply shocks account for somewhat more than ten percent on impact of the forecast error variance of real GDP growth. While the contribution of the business loan supply shock stays almost constant over the whole horizon, the household loan supply shock gains a bit in importance within the first year. In comparison, both shocks explain more than aggregate supply and monetary policy shocks and summed up they are as important as aggregate demand shocks after one year, which are the main driver of business cycle dynamics. Regarding the inflation rate, aggregate supply and demand shocks are the principal drivers with the two loan supply shocks playing a subordinate role, also at longer horizons. The forecast error variance of the federal funds rate is mostly explained by aggregate demand shocks, but household loan supply shocks become more important over time, whereas business loan supply shocks are of little relevance. As expected, both loan supply shocks account by far for the largest share of the forecast error variance of the corresponding loan volumes, while the three macroeconomic shocks seem to be only of modest importance. Interestingly, household loan supply shocks also explain a significant fraction in the growth rate of business loans at longer horizons. Finally, both loan rates are predominantly driven by aggregate demand shocks, even though household loan supply shocks account for a non-negligible part of both loan rates at longer horizons.

Taken together, both loan supply shocks appear to be significant drivers of the business cycle, with household loan supply shocks being a bit more important than business loan supply shocks. Despite explaining a similar fraction of real GDP growth forecast error variance, business loan supply shocks are only main drivers of business loan volume growth. Household loan supply shocks, on the other hand, seem to be relevant for the growth rates of both loan volumes, for both loan rates and the federal funds rate at longer horizons. In the chosen Median Target model (Table 3.5 in Appendix 3.C) household loans supply shocks turn out to explain even a significantly larger part of real GDP growth than business loan supply shocks, but otherwise the pattern is unchanged. Next, I look at the contributions of the two loan supply shocks to real GDP growth over the sample period.

Historical Decomposition The forecast error variance decomposition shows that considering the entire sample period both loan supply shocks are quantitatively important for real GDP growth. To figure out whether loan supply shocks have been particularly important during

Table 3.3: Forecast Error Variance Decomposition

Variable	*Horizon*	NFB Loan Supply	HH Loan Supply	Aggregate Supply	Aggregate Demand	Monetary Policy
Real GDP Growth	0	12.45	11.54	6.40	26.96	5.07
		[1.46 - 32.31]	[1.56 - 28.20]	[0.65 - 23.19]	[12.11 - 49.72]	[0.40 - 18.95]
	4	12.17	13.69	9.12	23.68	7.64
		[4.15 - 26.68]	[5.27 - 28.61]	[3.21 - 21.33]	[12.19 - 41.15]	[2.66 - 17.97]
	20	12.75	13.74	9.74	23.07	8.35
		[4.63 - 25.66]	[5.73 - 27.43]	[3.95 - 20.88]	[12.84 - 38.75]	[3.48 - 17.40]
Inflation Rate	0	0.00	0.00	15.11	15.84	9.96
				[2.14 - 40.53]	[2.61 - 46.69]	[1.02 - 33.91]
	4	3.14	2.92	13.65	21.35	8.97
		[1.40 - 6.38]	[1.19 - 5.53]	[4.53 - 34.43]	[7.06 - 42.03]	[3.30 - 25.15]
	20	3.92	5.31	13.47	22.23	8.96
		[1.73 - 8.55]	[2.14 - 10.78]	[4.78 - 30.09]	[7.54 - 39.36]	[3.61 - 20.81]
Federal Funds Rate	0	5.03	0.99	7.95	23.28	6.60
		[0.33 - 29.09]	[0.12 - 4.35]	[0.89 - 26.8]	[5.75 - 50.56]	[0.49 - 24.98]
	4	5.03	5.46	7.10	32.94	4.09
		[1.50 - 14.74]	[1.15 - 13.18]	[1.40 - 23.33]	[12.94 - 58.99]	[1.40 - 12.63]
	20	5.09	9.75	7.43	30.44	3.67
		[1.40 - 14.57]	[2.81 - 22.72]	[1.27 - 21.99]	[11.20 - 56.49]	[1.11 - 11.02]
NFB Loan Volume Growth	0	56.61	0.00	4.33	1.96	5.42
		[26.45 - 82.08]		[0.44 - 21.26]	[0.21 - 8.55]	[0.54 - 22.14]
	4	47.86	4.84	4.80	6.81	5.36
		[23.70 - 67.43]	[1.67 - 10.69]	[1.19 - 16.48]	[2.40 - 20.68]	[1.80 - 15.27]
	20	34.53	10.46	6.32	8.80	5.49
		[15.52 - 53.25]	[3.12 - 23.57]	[1.68 - 17.10]	[2.75 - 24.35]	[2.11 - 15.24]
NFB Loan Rate	0	8.26	0.00	8.79	20.99	6.76
		[0.61 - 33.33]		[0.89 - 28.72]	[3.49 - 50.11]	[0.80 - 24.73]
	4	5.14	3.49	7.58	34.38	3.97
		[1.61 - 13.92]	[0.71 - 9.01]	[1.54 - 23.91]	[14.07 - 60.28]	[1.36 - 12.86]
	20	5.04	8.46	7.59	31.52	3.52
		[1.50 - 14.71]	[2.16 - 19.99]	[1.41 - 22.56]	[12.08 - 57.53]	[1.12 - 10.84]
HH Loan Volume Growth	0	0.00	54.01	5.03	3.67	3.86
			[31.65 - 74.76]	[0.50 - 21.64]	[0.34 - 12.10]	[0.34 - 17.84]
	4	1.72	54.88	6.22	4.34	5.53
		[0.47 - 4.76]	[32.22 - 72.49]	[1.95 - 17.35]	[1.55 - 10.94]	[1.58 - 17.77]
	20	4.14	44.14	7.42	6.32	6.46
		[1.12 - 11.52]	[21.67 - 61.10]	[2.64 - 18.23]	[2.76 - 14.31]	[2.08 - 18.80]
HH Loan Rate	0	0.00	5.88	10.24	20.15	7.42
			[0.53 - 21.12]	[0.95 - 31.24]	[2.15 - 45.22]	[0.66 - 27.53]
	4	1.98	3.22	7.66	38.08	5.22
		[0.36 - 7.49]	[1.00 - 8.03]	[1.74 - 24.45]	[11.19 - 63.48]	[1.03 - 15.73]
	20	3.83	7.29	7.31	34.00	3.19
		[0.70 - 12.94]	[1.94 - 18.79]	[1.48 - 22.99]	[12.39 - 59.26]	[0.90 - 11.95]

Note: The table reports the posterior median contribution of the five identified shocks to the forecast error variance of the seven variables in the baseline model. Numbers in parentheses represent the contribution of the lower 16% and upper 84% percentile of the posterior distribution. Note that as the posterior median share is not associated with a single model, the explained shares by all shocks do not sum to one. As a comparison, Table 3.5 in Appendix 3.C states the forecast error variance decomposition of the Median Target model as proposed by Fry and Pagan (2011). See Table 3.4 in Appendix 3.B for definitions of variables.

some specific periods, I next present the series of structural loan supply shocks over time and then investigate the historical contribution of the two shocks to real GDP growth. The results presented in the following correspond to the median over all 1000 independent models, while Figure 3.18 in Appendix 3.C provides the historical decomposition with respect to the chosen Median Target model (Fry and Pagan, 2011).

Figure 3.4 depicts the median series of business and household loan supply shocks from the first quarter of 1985 onwards.[20] In the first years after 1985, one can see adverse loan supply shocks during the savings and loan crisis, with a pronounced negative household loan supply shock in 1986 and later a marked negative business loan supply shock during the recession in the early 1990s. After a more tranquil period with regard to loan supply shocks, starting in 1995 a series of positive business and medium-scale negative household loan supply shocks occurs. The former likely indicates favorable lending conditions for businesses during the build-up of the dot-com bubble, while the latter might be related to the Asian financial crisis and a reactive response of financial intermediaries to the resulting fall in long-term U.S. interest rates.[21] The bursting of the dot-com bubble can be recognized by a noticeable cluster of some modest negative business loan supply shocks between end-2000 and the beginning of 2003. Afterwards the mortgage boom becomes apparent by a prolonged series of positive household loan supply shocks between 2004 and 2005.[22] For households, lending conditions began to deteriorate already in 2006 in accordance with the decline in household loan growth rates (Figure 3.1), with a marked adverse shock in 2006Q4. The global financial crisis and the Great Recession are reflected in unprecedented negative loan supply shocks in 2008Q4, surrounded by some modest negative shocks. From then on there are no salient patterns anymore, with positive and negative loan supply shocks alternating until the end of the sample.

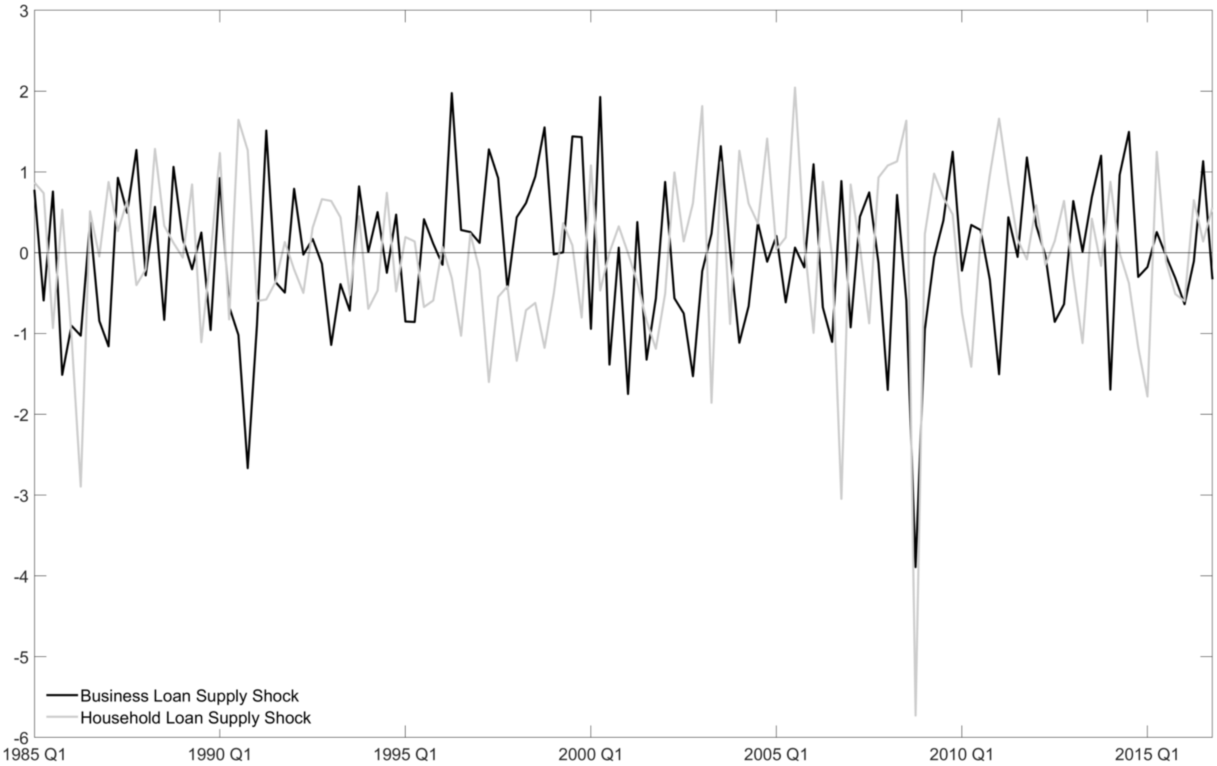
Figure 3.5 shows the contribution of the two loan supply shocks (gray bars) to real GDP growth (black line) over time. The general pattern mirrors by and large the series of loan supply shocks. Business loan supply shocks depressed real GDP growth around 1986 during the savings and loan crisis and particularly during the early 1990s recession, around and after the bust of the dot-com bubble in the early 2000s, and during the global financial crisis and the ensuing Great Recession. They contributed overwhelmingly positive to real GDP growth during the dot-com boom between 1995 and 2000. Household loan supply shocks had a negative effect on real GDP growth in 1986 as well, in the second half of the 1990s during the Asian financial crisis and other related crises, and from 2006 until the end of 2010 except some few quarters, as well as around 2015. Their contribution was on average positive between 1987 until the early 1990s, between 2003 and 2005, and 2011/12. During the last financial crisis, household loan supply shocks and business loan supply shocks had a similar cumulative negative effect on real GDP growth, with

[20] The first five years of the sample are left out due to the dependence on initial conditions.

[21] Spillover effects of the Asian financial crisis induced a fall in long-term U.S. interest rates, including mortgage rates. This led to an increase in mortgage refinancing during 1997 and 1999 according to the Mortgage Bankers Association refinance index (Duca et al., 1998, cf. also with Figure 5.2. in Justiniano et al., 2017). Technically, mortgage refinancing constitutes a household loan *demand* shock as borrowers apply for a new home loan to replace their existing one. A possible conjecture would then be that financial intermediaries loosened lending conditions for businesses during the dot-com boom, while at the same time the high demand for home loans prompted them to reduce the origination of *new* loans for households.

[22] Interestingly, the household loan supply shocks turn positive exactly around the time when mortgage rates disconnected from U.S. Treasury rates and employment figures of loan brokers kept on rising despite decreasing mortgage refinancing figures, suggesting that lenders were pushing for the origination of new mortgages (Justiniano et al., 2017, particularly Figure 5.2).

Figure 3.4: Business and Household Loan Supply Shock Series

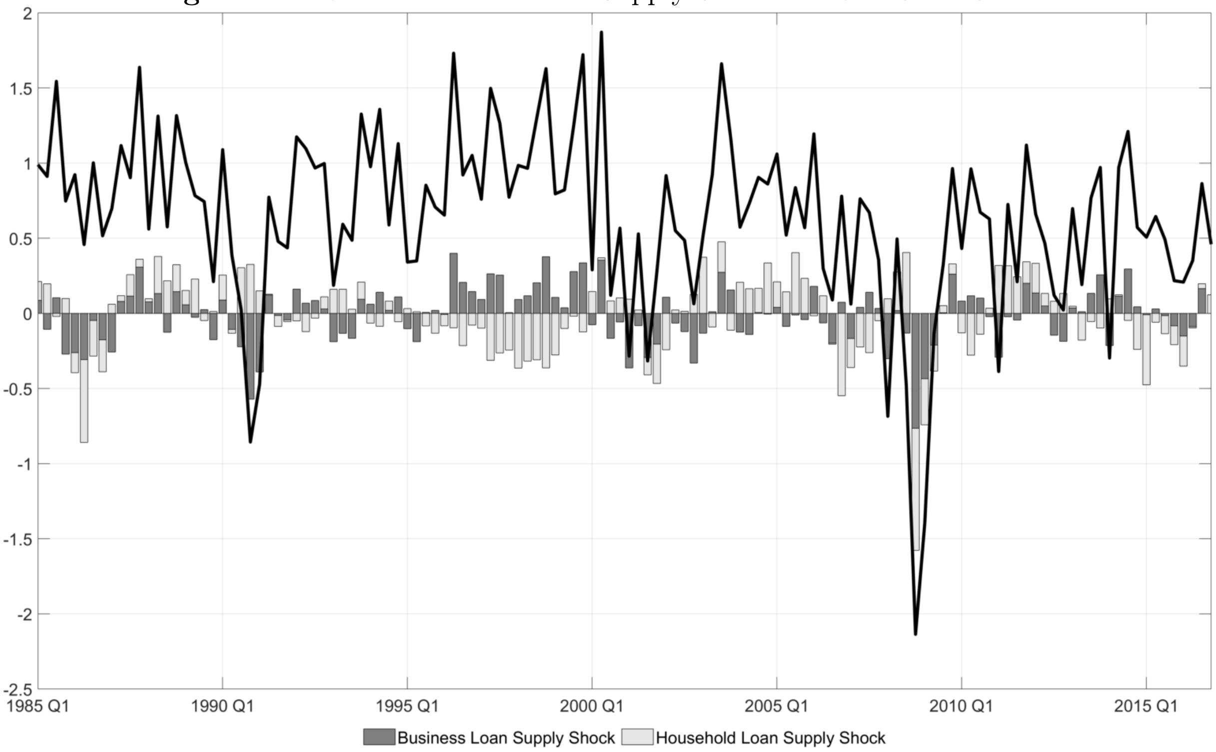


Note: The figure shows the median series of business (black) and household (gray) loan supply shocks over the period of 1985Q1 to 2016Q4. The first five years of the sample are left out due to the dependence on initial conditions. The vertical axis is in standard deviations.

the contribution of the former turning negative earlier. Household loan supply shocks depressed real GDP growth already between 2006Q4 and 2007Q4, when the U.S. housing boom ended and first signs of turmoil in the mortgage market became apparent. After three quarters with positive contributions, probably related to governmental rescue packages like the Housing and Economic Recovery Act of 2008 as well as takeovers and consolidation in the U.S. banking market, they adversely affected real GDP growth between 2008Q4 and 2009Q2. Business loan supply shocks were still slightly supporting output growth in 2007 and began to contribute negatively only in 2008. Added up, loan supply shocks explain a large part of the drop in real GDP growth during the peak of the crisis between 2008Q4 and 2009Q2.

As the median contributions are not associated with a single model, Figure 3.18 in Appendix 3.C presents the historical contribution of the two loan supply shocks to real GDP growth according to the Median Target model (Fry and Pagan, 2011). While the general pattern regarding the positive/negative contribution of the two loan supply shocks in a specific quarter is almost unchanged, the effects are quantitatively larger, especially for household loan supply shocks. For example, their negative contributions during the second half of the 1990s or in 2006-2007 as well as their positive impact in 2004-2005 are more pronounced. This is in accordance with the larger share in explaining real GDP growth according to the forecast error variance decomposition

Figure 3.5: Contribution of Loan Supply Shocks to Real GDP Growth



Note: The figure shows the median contribution of the two loan supply shocks (gray bars) to the actual growth rate of real GDP (black line) over the period of 1985Q1 to 2016Q4. The first five years of the sample are left out due to the dependence on initial conditions. The vertical axis is in percent.

of the Median Target model as compared to the median share across all models. Overall, the Median Target model and the median across all models suggest that both loan supply shocks have significantly affected real GDP growth during the sample period and have been especially important during the last global financial crisis and the subsequent Great Recession.

3.5.2 Results of the Extended Model Versions

This subsection presents results from some extended model versions in order to gain deeper insights on the transmission to and the impact on the macroeconomy of the two loan supply shocks. Specifically, an eighth variable is added to the seven variables included in the baseline model. These variables are real gross private domestic investment, real personal consumption expenditures, nonfarm employment, real house prices, and corporate bonds, all of which enter the model in first log-differences, as well as net exports and net private saving, which are expressed in percent of GDP. Depending on the variable, I either impose no restriction on their response to the loan supply shocks or a zero restriction (see Table 3.2 in Subsection 3.4.3 for details). I exclusively focus on the impulse responses of these additional variables to the two loan supply shocks; effects of the three macroeconomic shocks on these variables are shown in Figures 3.19 to 3.24 in Appendix 3.C.

Investment The first variable added to the baseline model is the growth rate of real gross private domestic investment, whose response to the two loan supply shocks is completely unrestricted. An adverse business loan supply shock causes a significant drop in real investment growth (more than -1 percentage points on impact), which is, however, again quite short-lived (Figure 3.6). In combination with the persistent effect on business loan growth, this result suggests that at least some firms are able to substitute loans with other forms of finance like corporate bonds (see below). Furthermore, it explains the short-lived and modest effect of business loan supply shocks on real output growth. Interestingly, an adverse household loan supply shock has a negative effect on real investment growth as well, although the 68% probability band is entirely below zero only for a very brief period about one quarter after the shock impact. This result, too, suggests that household loan supply shocks seem to depress aggregate demand and thereby prompt firms to invest less.

Consumption The response of real personal consumption expenditure growth to the two loan supply shocks is unrestricted as well. Still, an adverse household loan supply shock lowers real consumption growth by 0.2 percentage points on impact and fades out afterwards (Figure 3.7). In case of business loan supply shocks the posterior median response is negative as well, but the impact is quantitatively smaller and the 68% probability band is only marginally below zero for a brief period. In comparison to investment the effect on consumption is quantitatively much smaller on impact but at the same time more persistent. This is consistent with results from the effect of loan supply shocks in the Netherlands (Duchi and Elbourne, 2016). In general, consumption is less volatile than investment due to consumption smoothing by households, especially if households are able to draw on liquid asset holdings (Damar et al., 2014). Moreover, by far the largest part of U.S. household loans are mortgages (around 70% of total outstanding household loans on average over the sample period), which are predominantly used to purchase houses - a process not affecting consumption by the national accounts definition - and hence are less directly related to private consumption (Duchi and Elbourne, 2016).

Net Exports Bahadir and Gumus (2016) report that household credit exhibits a stronger positive correlation with real exchange rate appreciation and a stronger negative correlation with net exports than business credit in emerging market economies.[23] In order to explore if the two loan supply shocks have a different impact on net exports in the United States, I add the net exports-to-GDP ratio as an eighth variable to the baseline model and let its response unrestricted. Figure 3.8 shows that the household loan supply shock has no clear affect on net exports, while there is some indication that adverse business loan supply shocks raise the net exports-to-GDP ratio, with the 68% probability band entirely above zero roughly between the first and the third quarter after the shock impact.

[23] In their two-sector small open economy real business cycle model calibrated to Turkey, all positive sectoral credit shocks cause a decline in the net exports-to-GDP ratio, but due to a tighter credit limit for households the magnitude in response to household credit shocks is smaller.

Figure 3.6: Impulse Response of Real Gross Private Investment Growth to Loan Supply Shocks

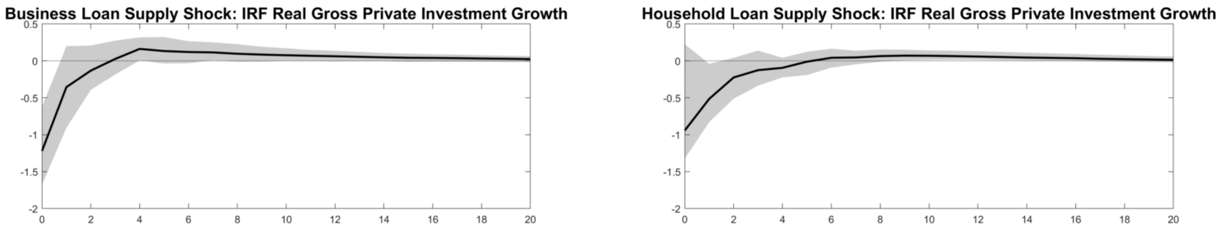


Figure 3.7: Impulse Response of Real Personal Consumption Growth to Loan Supply Shocks

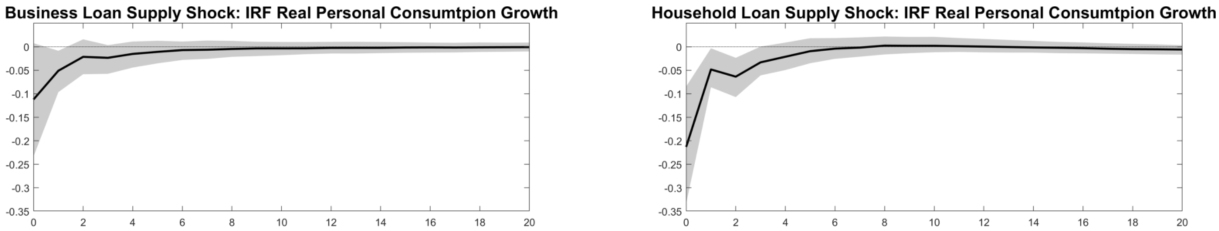
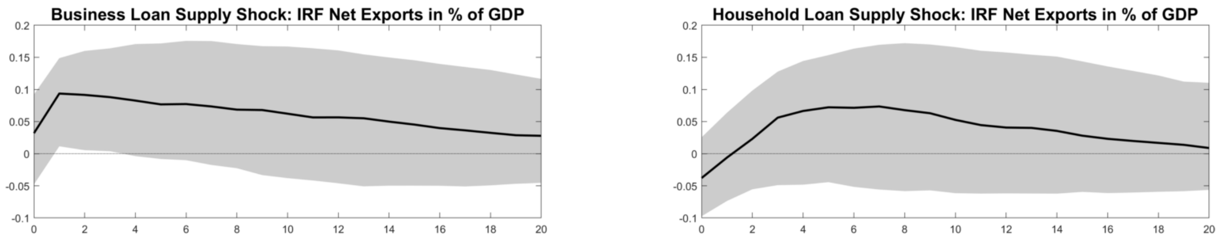


Figure 3.8: Impulse Response of Net Exports in % of GDP to Loan Supply Shocks



Note: Figures 3.6 to 3.8 show the posterior median impulse response of a respective eighth variable added to the baseline model to a negative, one-standard-deviation business loan supply shock (left column) and a negative, one-standard-deviation household loan supply shock (right column). These variables are real gross private investment, real personal consumption, and net exports in % of GDP. Shaded areas represent 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution of 500 draws that fulfill the restrictions. Vertical axes are in percentage points, horizontal axes are in quarters. See Table 3.4 in Appendix 3.B for definitions of variables.

Employment As another variable reflecting economic activity I add employment growth, measured as the quarterly percentage change in total nonfarm payrolls, as an eighth variable to the baseline model. Since employment is a slow-moving economic variable, I place an on-impact zero restriction in response to the two loan supply shocks. The posterior median impulse responses of employment growth square with the findings above: while both loan supply shocks shrink employment growth, the effect of a household loan supply shock is slightly more persistent (lasts for at least three quarters) than the one of a business loan supply shock which turns indeterminate less than two quarters after the shock has hit (Figure 3.9). Quantitatively, the household loan supply shock thus tends to have a bit larger cumulative effect, although the business loan supply shock has a stronger pointwise impact one quarter after the shock. Moreover, in both cases employment growth seems to rebound and even the whole 68% probability band gets marginally positive at longer horizons in case of household loan supply shocks. The cumulatively slightly more pronounced response of employment to a household loan supply shock is consistent with the result of Haltenhof et al. (2014) who find that households' access to bank loans matters more for employment in the manufacturing sector than firms' access to bank loans.

House Prices Some theoretical and empirical contributions find a close relationship between mortgage supply and house prices (Milcheva, 2013, Favara and Imbs, 2015, Justiniano et al., 2015, Di Maggio and Kermani, 2017, among others). As noted above, home mortgages account by far for the largest share of outstanding household loans over the sample period. In order to investigate whether household loan supply shocks exert an effect on house prices, I include the Case-Shiller House Price Index (deflated by the CPI to obtain real series) in the model. Since it takes time until an increase in the supply of loans, or more specifically mortgages, potentially translates into house prices, I impose an on-impact zero restriction on house prices. Results show that an adverse household loan supply shock has a short-lived and marginally negative effect on real house prices which turns indeterminate one quarter after the impact of the shock (Figure 3.10). This finding is thus largely in line with the aforementioned previous studies on the effect of mortgage supply on house prices as well as of mortgage spreads on house prices (Walentin, 2014). In contrast, real house prices exhibit virtually no response to business loan supply shocks.

Corporate Bonds There is evidence that firms with access to capital markets substitute loans with corporate bonds if the supply of loans is constrained (Adrian et al., 2012, Becker and Ivashina, 2014). This should mitigate the effects of business loan supply shocks on the macroeconomy. In order to analyze if this result also holds in the aggregate, I add the growth rate of corporate bonds as an eighth variable to the baseline model. As it takes some time until a new bond can be issued, it is plausible to assume a lagged response of corporate bonds to a loan supply shock and to place a zero restriction on the variable. Results reveal that an adverse business loan supply shock indeed has a positive effect on the growth of corporate bonds for just one quarter (Figure 3.11). Afterwards, the posterior median response turns negative, but the 68% probability band always includes zero. In response to a household loan supply shock there is no clear effect, even though the posterior median is consistently positive. Altogether, this result might indicate that some firms with access to capital markets indeed seem to be able to substitute loans with bonds in the quarter after a loan supply shock and thus contributes to the understanding of the short-lived effect of business loan supply shocks on investment and output.

Private Saving As a last investigation, I study the unrestricted response of net private saving in percent of GDP to the two loan supply shocks. This follows Jappelli and Pagano (1994) who show that rationing credit to households raises the saving rate and as a consequence in the long run output growth due to higher capital accumulation. The impulse response to the household loan supply shock confirms this finding (Figure 3.12): although the zero line is included in the 68% probability band at impact, it is above zero between the second and the fourteenth quarter

Figure 3.9: Impulse Response of Employment Growth to Loan Supply Shocks

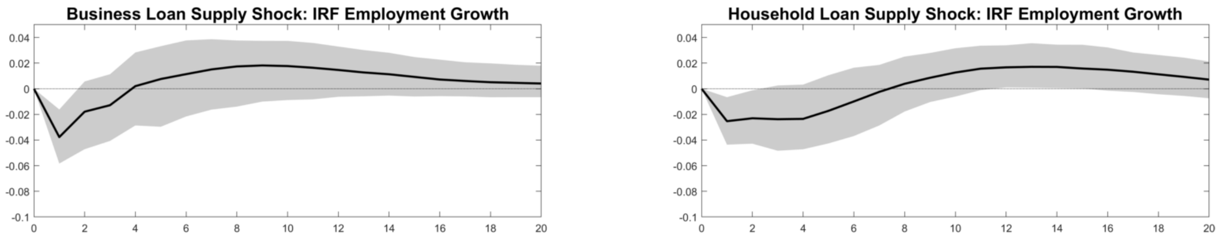


Figure 3.10: Impulse Response of Real House Prices Growth to Loan Supply Shocks

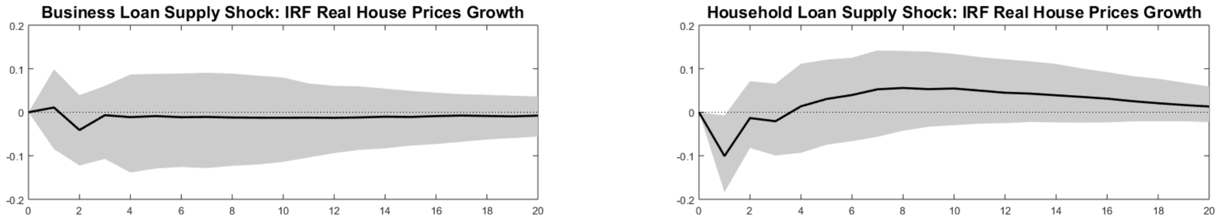


Figure 3.11: Impulse Response of Corporate Bonds Growth to Loan Supply Shocks

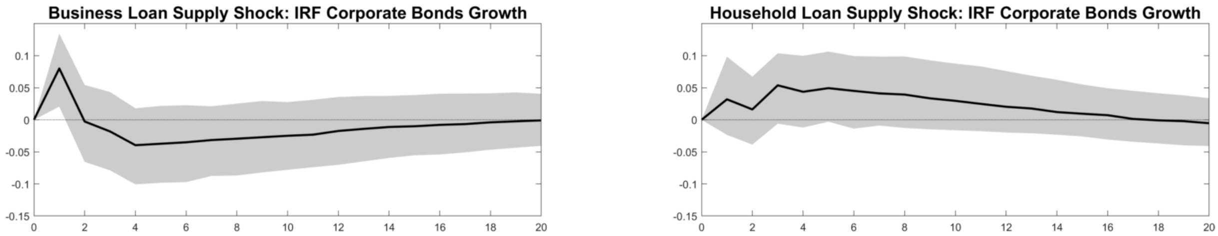
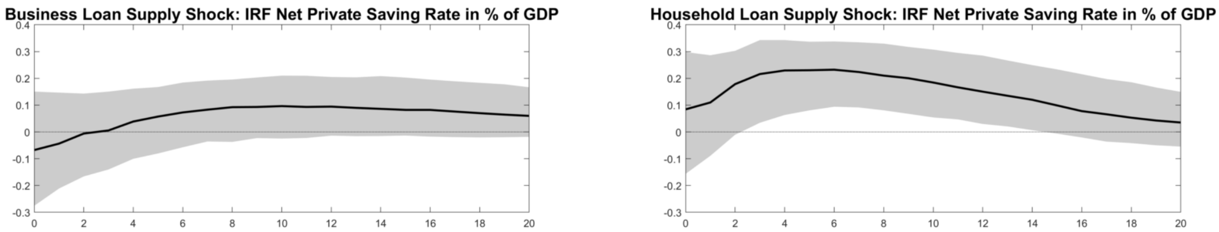


Figure 3.12: Impulse Response of Net Private Saving in % of GDP to Loan Supply Shocks



Note: Figures 3.9 to 3.12 show the posterior median impulse response of a respective eighth variable added to the baseline model to a negative, one-standard-deviation business loan supply shock (left column) and a negative, one-standard-deviation household loan supply shock (right column). These variables are employment, real house prices, corporate bonds, and net private saving in % of GDP. Shaded areas represent 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution of 500 draws that fulfill the restrictions. Vertical axes are in percentage points, horizontal axes are in quarters. See Table 3.4 in Appendix 3.B for definitions of variables.

after the shock has hit. The posterior median is positive for the whole horizon, pointing to a prolonged positive effect of household loan supply shocks on the net private saving ratio. The reaction to a business loan supply shock is indeterminate since the 68% probability band includes zero for the whole horizon, even if only marginally at longer horizons.

Summarizing, the results of the seven extended model versions substantiate that household loan supply shocks appear to resemble classical aggregate demand shocks. Besides driving output and inflation in the same direction, they have a negative effect on employment, consumption, and marginally on investment and real house prices, while raising the private saving ratio at medium horizons. The effects of business loan supply shocks are overall less persistent and for some variables more attenuated, but they still adversely affect investment, employment, as well as marginally also consumption, and slightly raise the net exports-to-GDP ratio. Negative business loan supply shocks further cause a short-lived increase in corporate bonds, suggesting that firms with access to capital markets seem to be partly able to substitute loans with corporate bonds in the immediate aftermath of the shock. This might explain the comparatively quick recovery of investment and output after an adverse business loan supply shock and is in contrast to households who are in principal only able to draw on liquid asset holdings to compensate for the reduced supply of loans.

3.5.3 Sensitivity Analysis of the Baseline Model

In this subsection, I briefly outline the results of some sensitivity analyses to the baseline model. While the identified shocks are almost identical with those from the baseline specification and qualitative results are also similar, there are sometimes quantitative differences. However, these quantitative differences make sense as, for example, loan supply shocks should have a smaller impact on real GDP growth if only bank loans, excluding mortgages, are considered. Detailed results of these sensitivity analyses are available upon request.[24]

Shorter Sample Period In a first sensitivity analysis I shorten the sample period to 1985Q1-2006Q4 to exclude the volatile first half of the 1980s as well as the global financial crisis and its aftermath. Results show that in this case the influence of household loan supply shocks on the business cycle is weaker in comparison to the baseline results. The impact effect on real GDP and household loans is smaller and the effects on the inflation rate and the federal funds rate almost vanish. This is also reflected in a smaller share of household loan supply shocks in the forecast error variance decomposition of real GDP growth. The effects of business loans supply shocks are very similar, with the exception that they now lead to a persistent negative effect on the federal funds rate. In sum, this suggests that household loan supply shocks seem to have been particularly important during and since the global financial crisis.

[24] Results of the specifications featuring the shadow monetary policy rate, loan spreads and bank loans are based on 500 independent draws that satisfy all restrictions. However, in case of a shorter sample size, longer restrictions and, in particular, additionally identifying loan demand shocks the number of draws to achieve a similar effective sample size gets excessively large. This is why for computational reasons results on the former two specifications are based on 100 independent draws and as few as 45 in case of the specification including loan demand shocks. This calls for caution in interpreting these results.

Shadow Monetary Policy Rate As the federal funds rate reached the zero lower bound during the global financial crisis and its aftermath, I estimate a model in which I replace it with the shadow rate constructed by Wu and Xia (2016). Using the shadow federal funds rate, which can take negative values, yields practically almost identical results. The only noticeable difference is that household loan supply shocks have a stronger negative effect on the shadow federal funds rate than on the normal one applied in the baseline model specification.

Loan Spreads Employing a loan spread instead of a pure loan rate in identifying loan supply shocks has the advantage of additionally capturing channels that operate neither via the quantity nor the price of loans, but comes at the cost of potentially also picking up changes in the spread that are due to changes in uncertainty or in the default risk of borrowers. In this robustness check, I replace both loan rates with a simple spread, calculated as the original loan rate minus the 3-month U.S. Treasury bill rate. Results indicate that business loan supply shocks have an effect on the federal funds rate as well as on the household loan spread in this case, while the impact on the business loan spread remains short-lived. Household loan supply shocks have a persistent effect on the household loan spread and a stronger effect on the federal funds rate, while they have no impact on the business loan spread. Regarding the forecast error variance of real GDP growth, business loan supply shocks become a bit more important in comparison to the baseline model specification. This is further reflected in a larger negative contribution to real GDP growth during the Great Recession between 2008Q4 and 2009Q2.

Bank Loans In this sensitivity analysis, I substitute the baseline loan measure with commercial and industrial loans from all commercial banks in case of businesses and consumer loans from all commercial banks in case of households. The former represent on average 25.61% of the business loan volume applied in the baseline specification over the sample period, while consumer loans from commercial banks constitute on average only 8.89% of total loans to households over the sample period. Given these figures, it is not surprising that in this sensitivity analysis results change the most. Household loan supply shocks have only a short-lived effect on real GDP growth and no impact on the inflation rate, the federal funds rate, the business loan volume and loan rate. This occurs despite a quantitatively larger impact of both loan supply shocks on the corresponding loan volume. Interestingly, in this specification business loan supply shocks exert a strong negative and prolonged effect on the household loan volume. Moreover, both loan supply shocks explain only half as much of the forecast error variance of real GDP growth as in the baseline model specification and except for the last financial crisis and the Great Recession they are quantitatively far less important for real GDP growth. In particular, the negative contributions of household loans supply shocks in the second half of the 1990s and the positive ones during the housing boom virtually vanish.

Longer Restrictions The baseline results suggest that both loan supply shocks mainly operate via a quantity channel, while the effect on loan rates is short-lived. In this robustness check, I investigate whether results change when the sign restrictions of the loan supply shocks are applied not only on impact but also on the first quarter following the shock. In this case, business loan supply shocks are found to have a clearer positive effect on the inflation rate and a marginally more persistent effect on real GDP growth. Further, they impact positively on the federal funds rate and lead to an increase of the business loan rate that lasts longer than the one found in the baseline model. There is little difference with respect to the impact of household loan supply shocks, whose effect on the household loan rate is still short-lived.

Loan Demand Shocks In a last robustness check, I additionally identify a business and a household loan demand shock, which are characterized by the same restrictions as the loan supply shocks apart from a negative sign on the corresponding loan rate. Note, however, that for computational reasons I do not place a magnitude restriction on the loan demand shocks according to which the impact on the loan volumes has to be greater than on real GDP growth. In comparison to the baseline model, the quantitative impact of the two loan supply shocks on real GDP growth shrinks a bit, while the impact on the corresponding loan volume stays the same. This is also apparent in a smaller share of the two loan supply shocks in the forecast error variance decomposition of real GDP growth and generally smaller contributions to it over the sample period, especially during the Great Recession between 2008Q4 and 2009Q2.

3.6 Concluding Remarks

The drastic fall in the supply of loans to the private sector during the global financial crisis of 2007 to 2009 has revived the interest of policymakers and researchers alike in the importance of financial intermediaries in affecting the business cycle. This paper contributes by providing a macroeconomic time series analysis that distinguishes between loan supply shocks affecting the business sector from those affecting the household sector in one structural model.

The results show that both loan supply shocks mainly operate through a quantitative channel, that is, they have a strong and prolonged effect on the corresponding loan volume, but almost none on the loan rate at short horizons. Despite having a similar effect on economic activity as measured by real GDP and employment in the first quarters after the shock impact, macroeconomic effects of household loan supply shocks are more persistent and thus cumulatively larger. Household loan supply shocks appear to resemble classical demand shocks since they depress inflation, provoke an easing of monetary policy, and also affect business loans over time. Moreover, they exhibit a significantly negative impact on consumption and marginally negative one on real house prices and investment. They also lead to a rise in the private saving rate at medium horizons. Business loan supply shocks, on the other hand, have a quite short-lived impact on investment and also marginal effects on consumption and on the net exports-to-GDP ratio around one quarter after the shock has hit. They further slightly affect the volume of corporate bonds in the short term as firms with access to capital markets seem to be able to substitute loans with corporate bonds at least partly. Finally, forecast error variance decompositions and a historical decomposition reveal that both loan supply shocks have contributed significantly to business cycle dynamics over the sample period, especially during the Great Recession following the global financial crisis. Having said this, results from sensitivity analyses suggest that in case of household loan supply shocks it is the drop in home mortgages during the global financial crisis that seems to be a main driver behind these findings.

In sum, these results point to the relevance of household finance for the U.S. macroeconomy. This substantiates theoretical and empirical works alike that stress the importance of household deleveraging for the economy (Mian and Sufi, 2010b, 2011, Eggertsson and Krugman, 2012, Mian et al., 2013, Guerrieri and Lorenzoni, 2017, Mian et al., 2017, Jones et al., 2018). In particular, Mian et al. (2017) emphasize the predominant role of the household sector in materializing the real effects of positive credit supply shocks through consumption booms over firm-debt driven investment booms. The contraction in household loans during the Great Recession contributed to the massive drop in U.S. economic activity and it seems that stabilizing the supply of loans to the household sector, and not only to the business sector, during times of financial turmoil might therefore be beneficial. At the same time, one should always bear in mind the consequences of excessive increases in household debt for financial and macroeconomic stability in the medium to long run. As studies have shown, in contrast to business loans, household loans are not associated with GDP growth in the long run and excessive growth of them is more likely related to subsequent banking crises (Büyükkarabacak and Valev, 2010, Beck et al., 2012, Angeles, 2015, Mian et al., 2017). Furthermore, it is essential to remember that the U.S. may be a special case as household loans make up more than half of total outstanding loans and businesses can take advantage of liquid capital markets to issue debt securities. Further research should therefore also investigate the relative macroeconomic impacts of business and household loan supply shocks in other countries or economic areas such as the eurozone.

3.A Technical Appendix

This appendix provides a more detailed technical description of the algorithm by Arias et al. (2018) applied to independently draw from the posterior distribution over the structural parameterization conditional on the imposed sign and zero restrictions. The description is entirely taken from Arias et al. (2018); see their paper for full details and underlying theorems and proofs thereof.

First, given that one wants to make draws from the structural parameterization $(\mathbf{A}_0, \mathbf{A}_+)$, while drawing is more convenient from the orthogonal reduced-form representation $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$, one needs to transform $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ into $(\mathbf{A}_0, \mathbf{A}_+)$. This is achieved by a mapping f_h given by

$$f_h(\mathbf{A}_0, \mathbf{A}_+) = (\underbrace{\mathbf{A}_+\mathbf{A}_0^{-1}}_{\mathbf{B}}, \underbrace{(\mathbf{A}_0\mathbf{A}_0')^{-1}}_{\mathbf{\Sigma}}, \underbrace{h((\mathbf{A}_0\mathbf{A}_0')^{-1})\mathbf{A}_0}_{\mathbf{Q}}),$$

where h denotes the Cholesky decomposition. That is, densities over the orthogonal reduced-form parameterization induce densities over the structural parameterization via the function f_h. The function f_h is invertible, with its inverse defined by

$$f_h^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) = (\underbrace{h(\mathbf{\Sigma})^{-1}\mathbf{Q}}_{\mathbf{A}_0}, \underbrace{\mathbf{B}h(\mathbf{\Sigma})^{-1}\mathbf{Q}}_{\mathbf{A}_+}).$$

Moreover, note that for the reduced-form representation of the VAR model in Equation (3.3), the normal-inverse-Wishart family of distributions is conjugate. A normal-inverse-Wishart distribution over the reduced-form parameters is characterized by four parameters: a scalar $\nu \geq n$, an $n \times n$ symmetric and positive definite matrix $\mathbf{\Phi}$, an $m \times n$ matrix $\mathbf{\Psi}$, and an $m \times m$ symmetric and positive definite matrix $\mathbf{\Omega}$. The distribution is denoted by $\mathrm{NIW}(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})$ and its density by $\mathrm{NIW}_{(\nu,\mathbf{\Phi},\mathbf{\Psi},\mathbf{\Omega})}(\mathbf{B}, \mathbf{\Sigma})$. If $\pi(\mathbf{Q}|\mathbf{B}, \mathbf{\Sigma})$ is the uniform density over the set of all $n \times n$ orthogonal matrices, then prior densities of the form $\mathrm{NIW}_{(\nu,\mathbf{\Phi},\mathbf{\Psi},\mathbf{\Omega})}(\mathbf{B}, \mathbf{\Sigma})\pi(\mathbf{Q}|\mathbf{B}, \mathbf{\Sigma})$ will be conjugate. Arias et al. (2018) call this the uniform-normal-inverse-Wishart distribution over the orthogonal reduced-form parameterization, denoted by $\mathrm{UNIW}(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})$ and with density $\mathrm{UNIW}_{(\nu,\mathbf{\Phi},\mathbf{\Psi},\mathbf{\Omega})}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$.

Arias et al. (2018) further show that if we independently draw $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ from this uniform-normal-inverse-Wishart distribution over the orthogonal reduced-form parameterization and apply f_h^{-1} to transform the draws to $(\mathbf{A}_0, \mathbf{A}_+)$, then we are in fact independently drawing from the density of what the authors call a normal-generalized-normal distribution over the structural parameterization, denoted by $\mathrm{NGN}(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})$ and with density $\mathrm{NGN}_{(\nu,\mathbf{\Phi},\mathbf{\Psi},\mathbf{\Omega})}(\mathbf{A}_0, \mathbf{A}_+)$.

Finally, we can now formulate the importance sampler algorithm that independently draws from the $\mathrm{NGN}(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})$ distribution over the structural parameterization conditional on the sign and zero restrictions. Steps 1 to 4 are based on *Algorithm 2* in Arias et al. (2018, pp. 697-698) and steps 5 to 7 on *Algorithm 3* in Arias et al. (2018, p. 700).

1. Draw $(\mathbf{B}, \mathbf{\Sigma})$ independently from the $\mathrm{NIW}(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})$ distribution.

2. For $1 \leq j \leq n$, draw $\mathbf{x}_j \in \mathbb{R}^{n+1-j-z_j}$ independently from a standard normal distribution and set $\mathbf{w}_j = \mathbf{x}_j / \|\mathbf{x}_j\|$. z_j corresponds to the row dimension of the matrix $\mathbf{Z}_j$ that defines the zero restrictions; see below.

3. Define $\mathbf{Q} = [\mathbf{q}_1 \cdots \mathbf{q}_n]$ recursively by $\mathbf{q}_j = \mathbf{K}_j \mathbf{w}_j$ for any matrix $\mathbf{K}_j$ whose columns form an orthonormal basis for the null space of the $(j-1+z_j) \times n$ matrix

$$\mathbf{M}_j = [\mathbf{q}_1 \ \cdots \ \mathbf{q}_{j-1} \quad (\mathbf{Z}_j \mathbf{F}(f_h^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{I}_n)))']'.$$

The $z_j \times r$ matrix $\mathbf{Z}_j$, where $0 \leq z_j \leq n-j$ for $1 \leq j \leq n$, defines the zero restrictions on the jth structural shock for $1 \leq j \leq n$ such that $\mathbf{Z}_j \mathbf{F}(\mathbf{A}_0, \mathbf{A}_+)\mathbf{e}_j = \mathbf{0}$ for $1 \leq j \leq n$, where $\mathbf{e}_j$ is the jth column of the identity matrix $\mathbf{I}_n$ and $\mathbf{F}(\mathbf{A_0}, \mathbf{A}_+)$ is any function from the structural parameters to the space of $r \times n$ matrices that satisfies the condition $\mathbf{F}(\mathbf{A_0 Q}, \mathbf{A}_+\mathbf{Q}) = \mathbf{F}(\mathbf{A_0}, \mathbf{A}_+)\mathbf{Q}$, which is true for impulse response functions. Hence, the zero restrictions in the orthogonal reduced-form parameterization are $\mathbf{Z}_j \mathbf{F}(f_h^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}))\mathbf{e}_j = \mathbf{Z}_j \mathbf{F}(f_h^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{I}_n))\mathbf{Q}\mathbf{e}_j = \mathbf{0}$.

4. Set $(\mathbf{A}_0, \mathbf{A}_+) = f_h^{-1}(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$.

5. If $(\mathbf{A}_0, \mathbf{A}_+)$ satisfies the sign (and magnitude) restrictions, set its importance weight to

$$\frac{\mathrm{NGN}_{(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})}(\mathbf{A_0}, \mathbf{A}_+)}{\mathrm{NIW}_{(\nu, \mathbf{\Phi}, \mathbf{\Psi}, \mathbf{\Omega})}(\mathbf{B}, \mathbf{\Sigma}) \ v_{(g \circ f_h)|\mathcal{Z}}(\mathbf{A}_0, \mathbf{A}_+)} \propto \frac{|\det(\mathbf{A}_0)|^{-(2n+m+1)}}{v_{(g \circ f_h)|\mathcal{Z}}(\mathbf{A}_0, \mathbf{A}_+)},$$

where $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) = f_h(\mathbf{A}_0, \mathbf{A}_+)$, $\mathcal{Z}$ denotes the set of all structural parameters that satisfy the zero restrictions, and $v_{(g \circ f_h)}(\mathbf{A}_0, \mathbf{A}_+)$ is the volume element of the composite function $g \circ f_h$ at $(\mathbf{A}_0, \mathbf{A}_+)$. $g(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q})$ represents a differentiable function $g : V \to \mathbb{R}^{nm+n^2+\sum_{j=1}^{n}(n+1-j-z_j)}$ with open set $V \subset \mathbb{R}^{nm+n^2+n^2}$ such that the functions $\mathbf{K}_j = \mathbf{K}_j(\mathbf{B}, \mathbf{\Sigma}, \mathbf{q}_1, \ldots, \mathbf{q}_{j-1})$ can be defined so that they are differentiable for all $(\mathbf{B}, \mathbf{\Sigma}, \mathbf{Q}) \in V$. On the other hand, if $(\mathbf{A}_0, \mathbf{A}_+)$ violates any sign (or magnitude) restriction, set its importance weight to zero.

6. Return to Step 1 until the required number of draws has been obtained.

7. Re-sample with replacement using the importance weights.

I set the required number of draws such that I obtain an effective sample size of at least 1000 draws in case of the baseline model and at least 500 draws in case of the extended model versions. The effective sample size is given by $\left(\sum_{i=1}^{N} \omega_i\right)^2 / \left(\sum_{i=1}^{N} \omega_i^2\right)$, where ω_i is the weight associated with the ith draw and N denotes the total number of draws. It should be interpreted as the actual number of independent draws produced by the importance sampler and expressed as a share of the draws satisfying all restrictions it always lies between 0 and 1.

3.B Data Appendix

Table 3.4: Definition of Variables

Variable	Source and Construction
Real Gross Domestic Product	Federal Reserve Economic Data, St. Louis Fed. Series code: GDPMC1. Millions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate. First log-differences.
Consumer Price Index	Federal Reserve Economic Data, St. Louis Fed. Series code: CPIAUCSL. All Urban Consumers: All Items, Index 1982-1984=100, Quarterly, Seasonally Adjusted. First log-differences.
Federal Funds Rate	Federal Reserve Economic Data, St. Louis Fed. Series code: FEDFUNDS. Effective Federal Funds Rate, Percent, Quarterly, Not Seasonally Adjusted.
Business Loans	Flow of Funds Accounts of the United States, Z.1 Statistical Release. Nonfinancial business, loans. Unique identifier: Z1/Z1/FL144123005.Q. Millions of U.S. Dollars, Quarterly. Seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment. First log-differences.
Business Loan Rate	Composite lending rate. 1980Q1-1986Q2: Bank Prime Loan Rate 1986Q3-2016Q4: average of Bank Prime Loan Rate and Commercial and Industrial Loan Rate. Bank Prime Loan Rate: Federal Reserve Economic Data, St. Louis Fed. Series code: MPRIME. Percent, Quarterly, Not Seasonally Adjusted. Commercial and Industrial Loan Rate: Board of Governors of the Federal Reserve System. Survey of Terms of Business Lending. All loans, Percent, Quarterly, Not Seasonally Adjusted.
Household Loans	Flow of Funds Accounts of the United States, Z.1 Statistical Release. Households and nonprofit organizations, loans. Unique identifier: Z1/Z1/FL154123005.Q. Millions of U.S. Dollars, Quarterly. Seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment. First log-differences.
Household Loan Rate	Composite lending rate. Weighted average of mortgage rates and finance rates. Mortgage rates: average of 30-Year Conventional Mortgage Rate and 1-Year Adjustable Rate Mortgage Average in the United States. Since the latter is only available from 1984Q1 onwards, previous values are calculated applying the change of the 30-Year Conventional Mortgage Rate. Finance rates: average of Finance Rate on Consumer Installment Loans at Commercial Banks, New Autos 48 Month Loan and Finance Rate on Personal Loans at Commercial Banks, 24 Month Loan. Weights: quarterly share of home plus commercial mortgages in total household loans for mortgage rate and quarterly share of consumer credit plus depository institution loans n.e.c. plus other loans and advances in total household loans for finance rate. 30-Year Conventional Mortgage Rate: Federal Reserve Economic Data, St. Louis Fed. Series code: MORTG. Percent, Quarterly, Not Seasonally Adjusted. 1-Year Adjustable Rate Mortgage Average in the United States: Federal Reserve Economic Data, St. Louis Fed. Series code: MORTGAGE1US. Percent, Quarterly, Not Seasonally Adjusted. Finance Rate on Consumer Installment Loans at Commercial Banks, New Autos 48 Month Loan: Federal Reserve Economic Data, St. Louis Fed. Series code: TERMCBAUTO48NS. Percent, Quarterly, Not Seasonally Adjusted. Finance Rate on Personal Loans at Commercial Banks, 24 Month Loan: Federal Reserve Economic Data, St. Louis Fed. Series code: TERMCBPER24NS. Percent, Quarterly, Not Seasonally Adjusted.

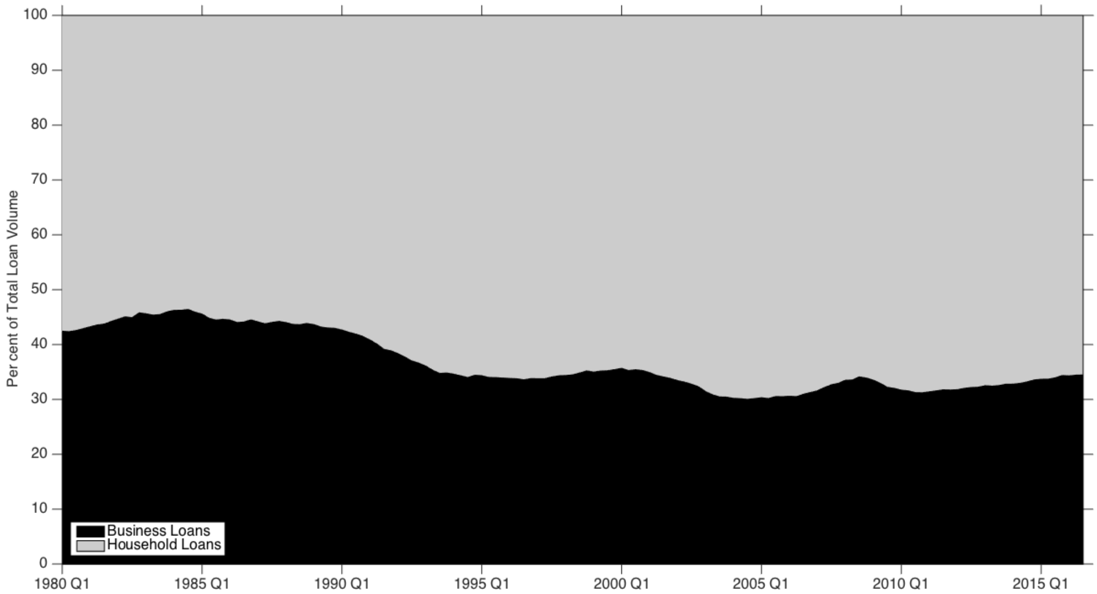
Employment	Federal Reserve Economic Data, St. Louis Fed. All Employees: Total Nonfarm Payrolls. Series code: PAYEMS. Thousands of Persons, Quarterly, Seasonally Adjusted. First log-differences.
Real Investment	Federal Reserve Economic Data, St. Louis Fed. Series code: GPDIC1. Real Gross Private Domestic Investment, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate. First log-differences.
Real Consumption	Federal Reserve Economic Data, St. Louis Fed. Series code: PCECC96. Real Personal Consumption Expenditures, Billions of Chained 2009 Dollars, Quarterly, Seasonally Adjusted Annual Rate. First log-differences.
Net Exports in % of GDP	Federal Reserve Economic Data, St. Louis Fed. Series code: NETEXP. Net Exports of Goods and Services, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate. In percent of Nominal GDP: Federal Reserve Economic Data, St. Louis Fed. Series code GDP. Gross Domestic Product, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate.
Real House Prices	Federal Reserve Economic Data, St. Louis Fed. Series code: CSUSHPISA. S&P/Case-Shiller U.S. National Home Price Index, Index January 2000 = 100, Quarterly, Seasonally Adjusted. Deflated by the Consumer Price Index (see above for its definition). First log-differences.
Corporate Bonds	Flow of Funds Accounts of the United States, Z.1 Statistical Release. Non-financial corporate business, corporate bonds. Unique identifier: Z1/Z1/FL103163003.Q. Millions of U.S. Dollars, Quarterly. Seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment. First log-differences.
Private Saving in % of GDP	Federal Reserve Economic Data, St. Louis Fed. Series code: W202RC1Q027SBEA. Net Private Saving, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate. In percent of Nominal GDP: Federal Reserve Economic Data, St. Louis Fed. Series code GDP. Gross Domestic Product, Billions of Dollars, Quarterly, Seasonally Adjusted Annual Rate. First log-differences.
Business Bank Loans	Federal Reserve Economic Data, St. Louis Fed. Series code: BUSLOANS. Commercial and Industrial Loans, All Commercial Banks, Billions of U.S. Dollars, Quarterly, Seasonally Adjusted. First log-differences.
Household Bank Loans	Federal Reserve Economic Data, St. Louis Fed. Series code: CONSUMER. Consumer Loans at All Commercial Banks, Billions of U.S. Dollars, Quarterly, Seasonally Adjusted. First log-differences.

Note: This table reports the variables used in baseline model specification, the extended model versions, and in the sensitivity analyses as well as their source and construction.

3.C Tables and Figures

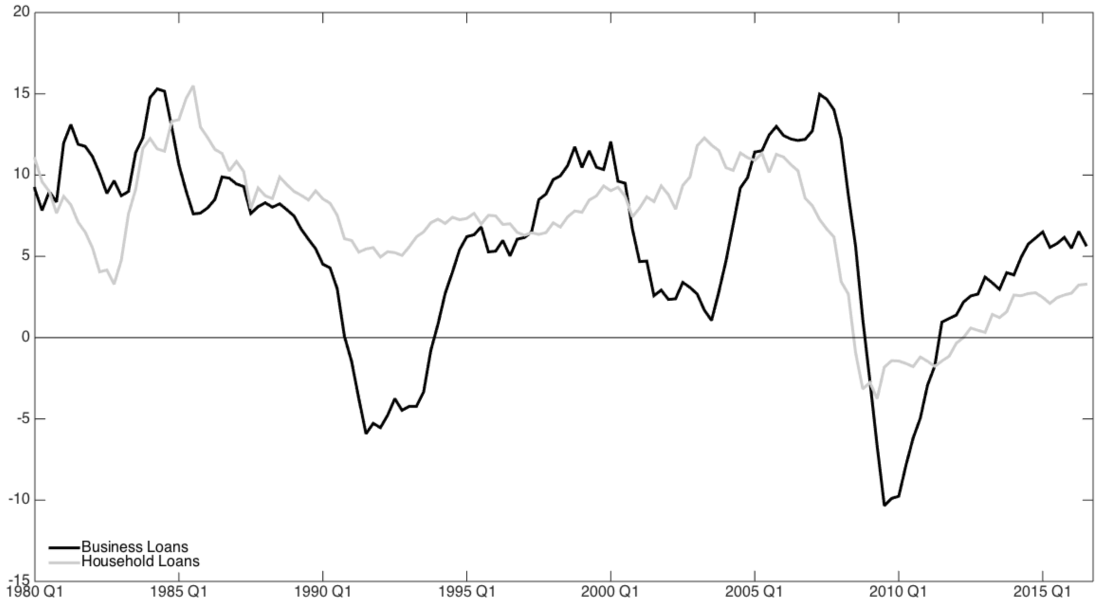
3.C.1 Stylized Facts Graphs

Figure 3.13: Shares of Business and Household Loans in Total Private Non-Financial Loans



Note: The figure shows the percentage shares of business (black) and household (gray) loans in total loans to the non-financial private sector over the sample period of 1980Q1 to 2016Q4. Business loans refer to the outstanding loan volume of non-financial businesses, household loans to the outstanding loan volume of households and nonprofit organizations. Data are obtained from the Flow of Funds Accounts of the United States; see Table 3.4 in Appendix 3.B for details.

Figure 3.14: Nominal Annual Growth Rates of Total Loans



Note: The figure shows the seasonally adjusted nominal annual growth rates of business (black line) and household (gray line) loans over the sample period of 1980Q1 to 2016Q4. Business loans refer to the outstanding loan volume of non-financial businesses, household loans to the outstanding loan volume of households and nonprofit organizations. Data are obtained from the Flow of Funds Accounts of the United States; see Table 3.4 in Appendix 3.B for details.

3.C.2 Impulse Responses to Macroeconomic Shocks in the Baseline Model

Figure 3.15: Impulse Responses to Aggregate Supply Shock

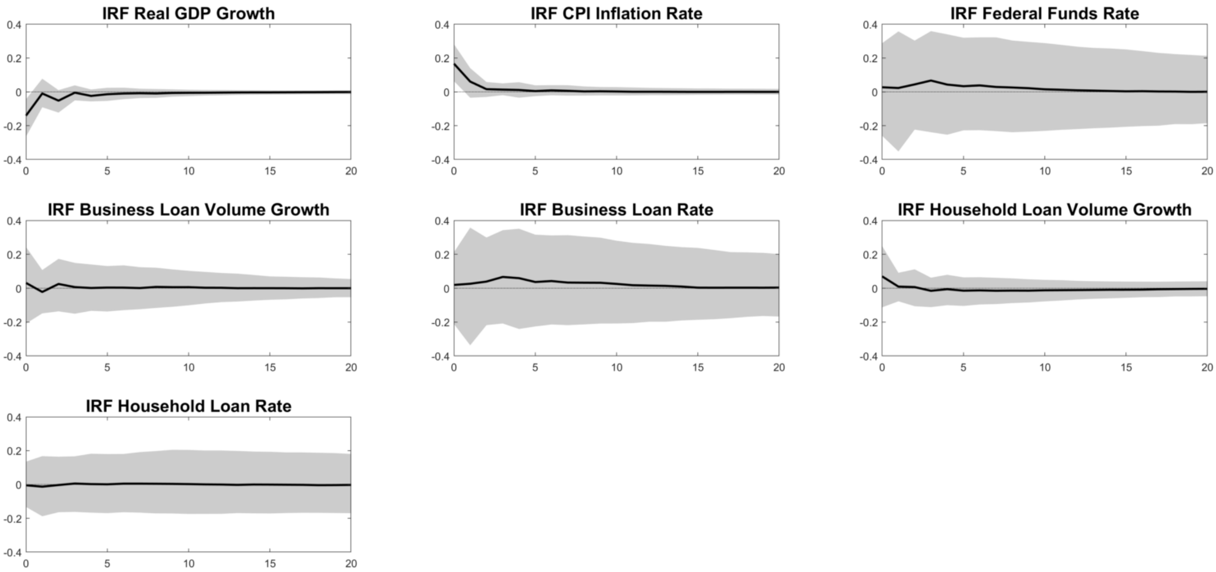
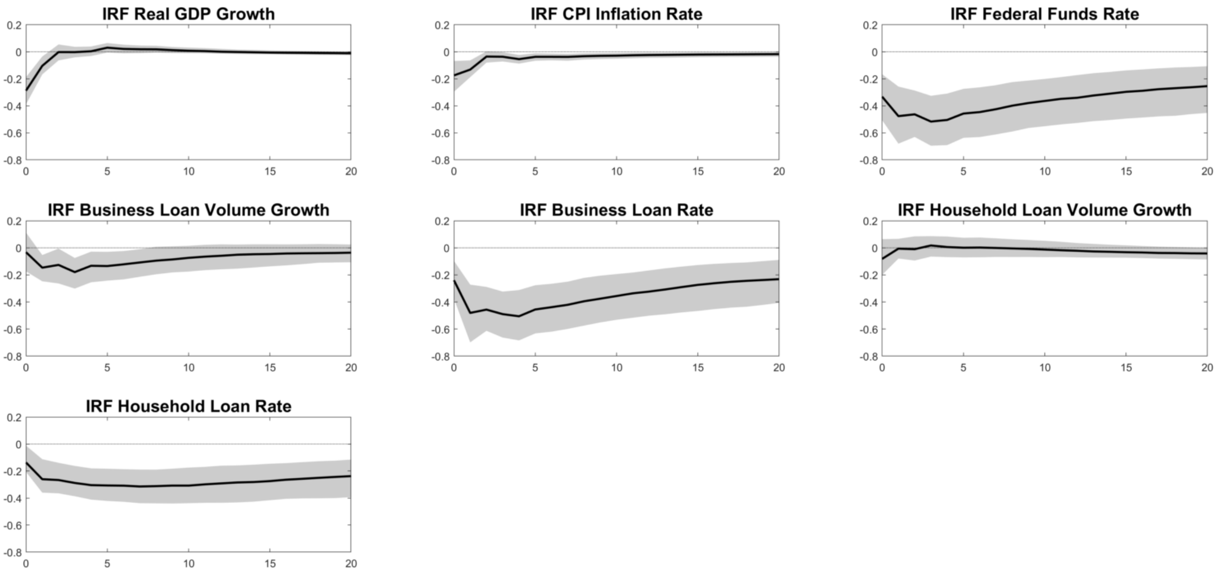
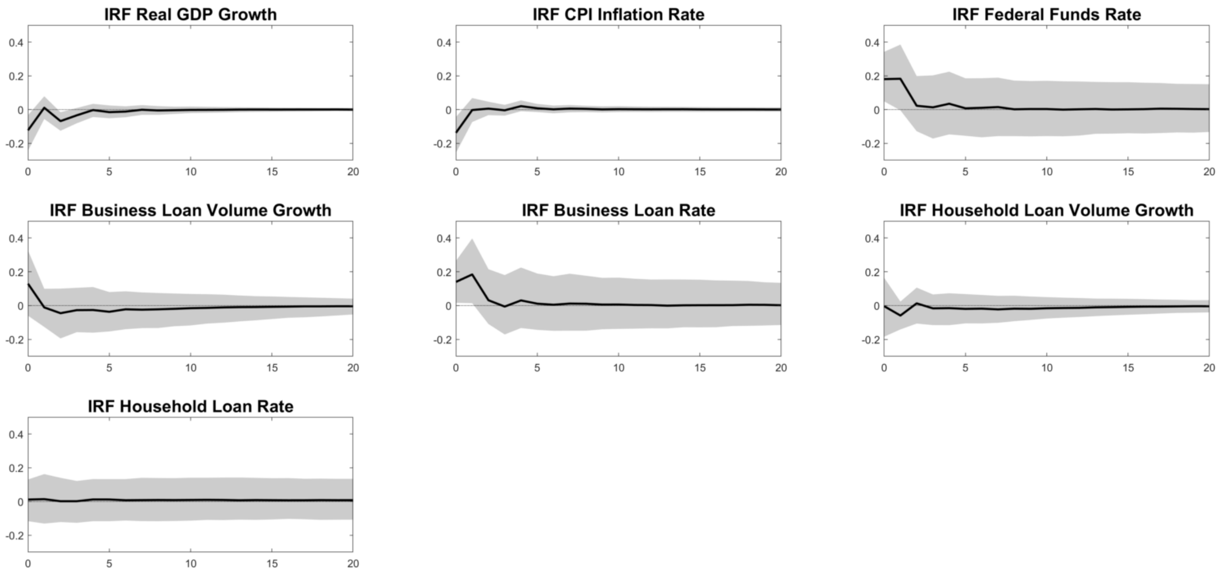


Figure 3.16: Impulse Responses to Aggregate Demand Shock



Note: Figures 3.15 and 3.16 show the posterior median impulse responses of the seven variables in the baseline model to a negative, one-standard-deviation aggregate supply and aggregate demand shock, respectively. Shaded areas represent 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution of all 1000 saved draws that fulfill the restrictions. Vertical axes are in percentage points, horizontal axes are in quarters. See Table 3.4 in Appendix 3.B for definitions of variables.

Figure 3.17: Impulse Responses to Monetary Policy Shock



Note: Figure 3.17 shows the posterior median impulse responses of the seven variables in the baseline model to a negative, one-standard-deviation monetary policy shock. Shaded areas represent 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution of all 1000 saved draws that fulfill the restrictions. Vertical axes are in percentage points, horizontal axes are in quarters. See Table 3.4 in Appendix 3.B for definitions of variables.

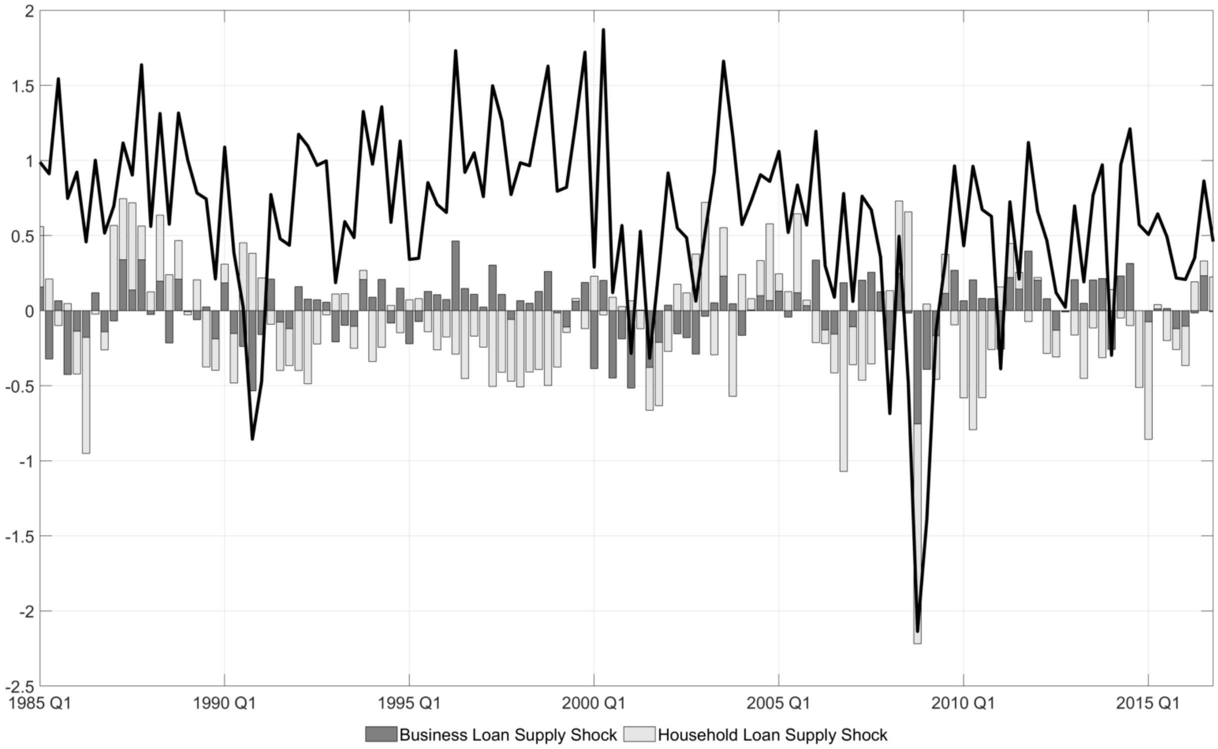
3.C.3 Median Target Model Results

Table 3.5: Forecast Error Variance Decomposition - Median Target Model

Variable	*Horizon*	NFB Loan Supply	HH Loan Supply	Aggregate Supply	Aggregate Demand	Monetary Policy	Unidentified Shocks
Real GDP	0	13.03	28.96	4.04	29.12	21.67	3.18
Growth	4	9.81	25.38	10.71	28.15	16.94	9.01
	20	10.14	24.76	10.77	27.78	17.06	9.49
CPI Inflation	0	0.00	0.00	29.46	7.49	24.53	38.53
Rate	4	3.24	4.32	25.99	21.94	20.65	23.87
	20	3.41	5.30	24.27	25.57	19.68	21.77
Federal Funds	0	0.56	0.46	13.33	71.41	9.69	4.55
Rate	4	1.22	7.65	15.84	64.98	3.01	7.30
	20	1.05	12.59	9.71	64.81	1.64	10.20
NFB Loan	0	86.85	0.00	1.96	4.96	3.99	2.24
Volume Growth	4	72.21	7.11	1.19	9.50	4.40	5.58
	20	62.81	11.32	1.51	11.11	3.38	9.86
NFB Loan Rate	0	1.70	0.00	1.33	75.62	17.73	3.61
	4	1.30	5.95	12.05	70.60	4.62	5.48
	20	1.11	11.91	8.32	67.34	2.71	8.61
HH Loan	0	0.00	44.89	8.11	0.62	0.49	45.89
Volume Growth	4	0.35	46.80	5.48	3.07	0.91	43.39
	20	1.19	41.92	4.75	3.87	3.91	44.36
HH Loan Rate	0	0.00	17.22	2.32	36.60	7.54	36.32
	4	0.03	3.30	3.88	64.90	5.58	22.31
	20	0.04	7.94	7.17	68.68	1.47	14.70

Note: The table reports the contribution of the five identified and two unidentified shocks to the forecast error variance of the seven variables according to the Median Target model (Fry and Pagan, 2011), taking into account the impact and the first year afterwards. See Table 3.4 in Appendix 3.B for definitions of variables.

Figure 3.18: Historical Decomposition of Real GDP Growth - Median Target Model



Note: The figure shows the contribution of the two loan supply shocks to the actual growth rate of real GDP over the period of 1985Q1 to 2016Q4 according to the Median Target model (Fry and Pagan, 2011), taking into account the impact and the first year afterwards. The first five years of the sample are left out due to the dependence on initial conditions. The vertical axis is in percent.

3.C.4 Impulse Responses to Macroeconomic Shocks in the Extended Models

Figure 3.19: Impulse Response of Real Investment Growth to Macroeconomic Shocks

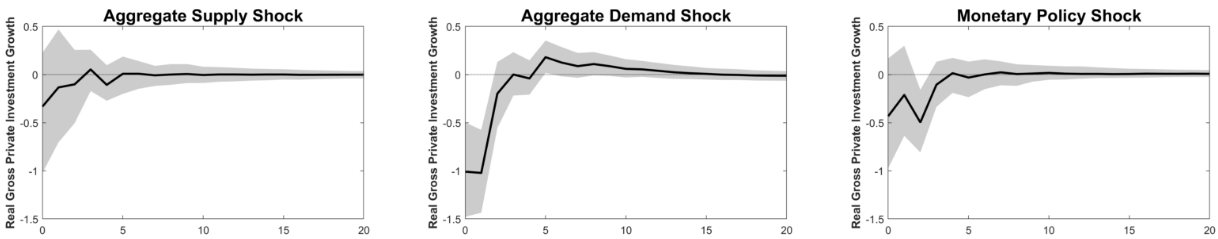


Figure 3.20: Impulse Response of Real Consumption Growth to Macroeconomic Shocks

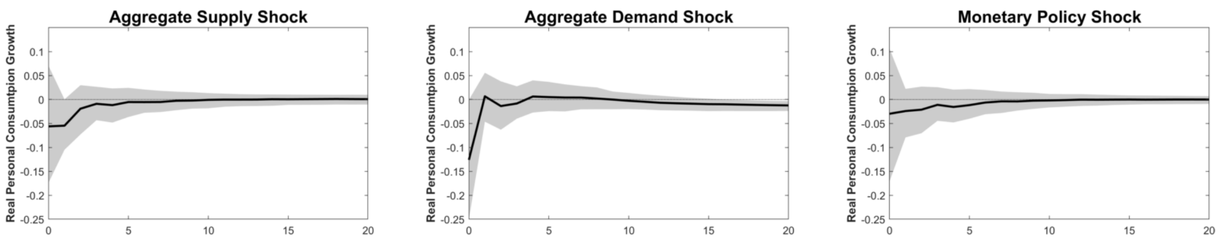


Figure 3.21: Impulse Response of Net Exports in % of GDP to Macroeconomic Shocks

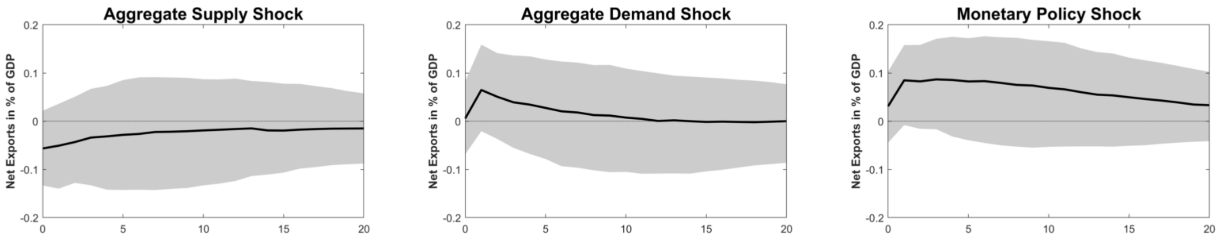


Figure 3.22: Impulse Response of Real House Prices Growth to Macroeconomic Shocks

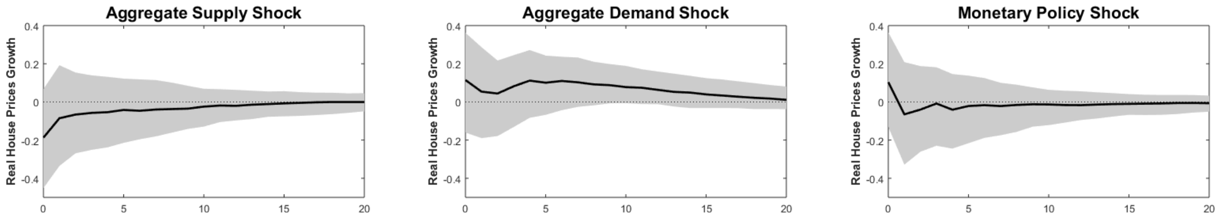


Figure 3.23: Impulse Response of Corporate Bonds Growth to Macroeconomic Shocks

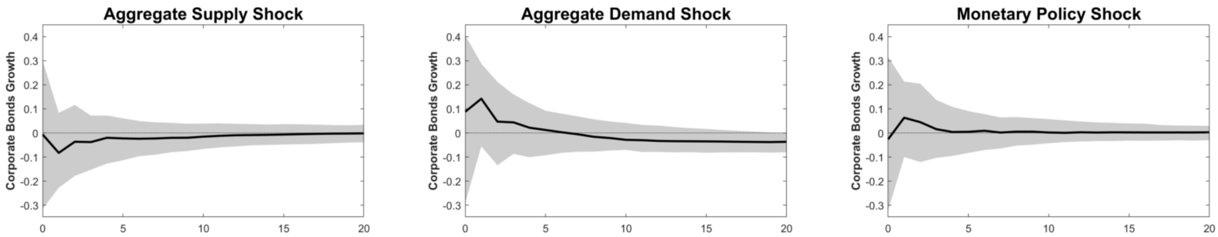
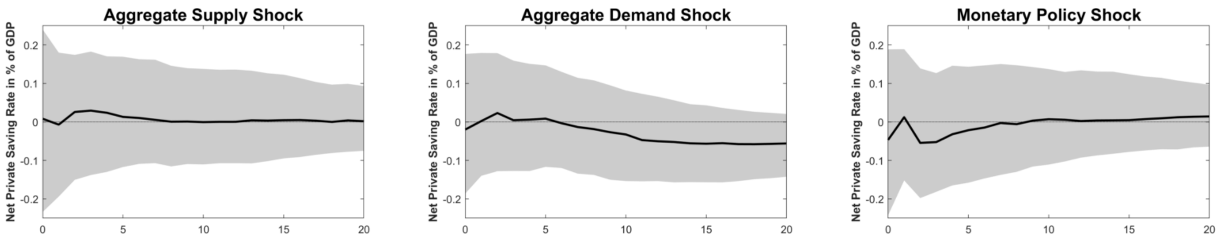


Figure 3.24: Impulse Response of Net Private Saving in % of GDP to Macroeconomic Shocks



Note: Figures 3.19 to 3.24 show the posterior median impulse responses of a respective eighth variable added to the baseline model to a negative, one-standard-deviation aggregate supply, aggregate demand, and monetary policy shock, respectively. Shaded areas represent 68% point-wise probability bands obtained from taking the 16% and 84% percentile of the posterior distribution of all 1000 saved draws that fulfill the restrictions. Vertical axes are in percentage points, horizontal axes are in quarters. See Table 3.4 in Appendix 3.B for definitions of variables.

CHAPTER 4

Global European Banks and the Global Financial Cycle

4.1 Introduction

European banks are key actors in the global financial system and have crucially shaped global financial conditions in the last two decades. Prior to the global financial crisis, European banks were expanding their balance sheets substantially and in particular were increasing their cross-border lending to both advanced and emerging economies. They were heavily engaged in credit intermediation via structured securities in the U.S. and were important lenders to other regions like Eastern Europe, Asia, and Latin America, either directly or indirectly via local branches and affiliates (Shin, 2012, Cerutti et al., 2017). Moreover, they played a major role in complex finance areas like trade or project finance (Feyen and del Mazo, 2013). The shockwaves of the global financial crisis and repercussions of the sovereign debt crisis in the eurozone just a few years later hit European banks hard and forced them to deleverage and adjust their business model. This caused concerns among policymakers and academics regarding the impact of European banks' retrenchment and adverse spillover effects. Almost ten years after the global financial crisis, European banks have shrunk significantly their balance sheets, but have maintained their geographical reach (Schoenmaker, 2017).

Given these observations, it is essential to learn about the global effects of shocks originating in the balance sheet of large European banks. In this paper, I propose a simple approach to identify structural supply-side balance sheet shocks to European banks within a time series framework and study its international spillovers in a global vector autoregressive (GVAR) model. Specifically, I run a panel regression on the leverage ratio of more than 30 large European banks to partial out country-specific and global macro-financial conditions as well as bank-individual factors. Then, I aggregate the estimated residuals to construct an exogenous time-series measure of fundamentally unexplained shifts in the leverage of large European banks that serves as a proxy for balance sheet shocks. Intuitively, the shock can be interpreted either as an exogenous change in a bank's ability to raise funding in the market, or in a bank's risk assessment owing to alterations in its own perception of risk and monitoring incentives or due to regulatory requirements. Both scenarios affect a bank's leverage as well as potentially, but not necessarily, its supply of credit.[1] In a next step, I apply the proxy as an external instrument to identify the structural balance sheet shock (Stock and Watson, 2012, Mertens and Ravn, 2013) in a GVAR model consisting of 30

[1] Note that there are several ways how banks can adjust their leverage, including one in which the asset side of the balance sheet and hence its supply of credit is unchanged (Gross et al., 2016). It is therefore important to be aware of the difference to traditional sign-identified credit supply shocks.

advanced and emerging economies over the period 1999Q1 to 2016Q4. In focusing on the effects of variables associated with the global financial cycle (Rey, 2013), I consider two specifications of the GVAR model, one including gross capital inflows and one real credit growth. Summing up, the paper aims to learn about the global effects of the observed leverage cycle of large European banks during the last two decades.

The paper contributes to the literature in several ways. First, to the best of my knowledge this is the first paper that analyzes international spillovers of structural shocks to the balance sheet of large European banks to advanced and emerging economies within a GVAR model. This is surprising given the important role of European banks for global financial conditions (Acharya and Schnabl, 2010, Shin, 2012, Ivashina et al., 2015, Cerutti et al., 2017) and sophisticated finance areas like trade or project finance that require profound experience and knowledge and thus are hard to substitute by others (Feyen and del Mazo, 2013). Assessing international spillovers of deleveraging of European banks not only contributes to the understanding of the global financial crisis and the global financial cycle (Rey, 2013), but it is moreover of interest to policymakers and regulators. Related works either limit their analysis to Europe (Gross et al., 2016, 2017) or study a single sign-identified credit supply shock (Eickmeier and Ng, 2011, Fadejeva et al., 2015), thereby ignoring the possibility of different ways of how banks can adjust their leverage and how their supply of credit is affected by this. In contrast to these works, I identify a balance sheet shock without imposing sign restrictions on the response of any endogenous variable and study its global spillovers and not only its impact in European countries. The advantage of not imposing sign restrictions is particularly relevant in this specific context as, for example, it is a priori not clear if large European banks deleverage by cutting back lending in their domestic country and the euro area or if there is a home bias effect (Giannetti and Laeven, 2012a,b), implying that cross-border lending is curtailed while lending at home is not or only mildly affected.

Second, the paper demonstrates a simple and straightforward way of constructing and employing an external instrument to identify a structural supply-side balance sheet shock to large European banks. The basic idea for deriving a measure proxying exogenous bank balance sheet shocks follows previous work by Hancock and Wilcox (1993, 1994), Berrospide and Edge (2010), Mésonnier and Stevanovic (2012), Bassett et al. (2014), and Altavilla et al. (2015), who purge either bank capital measures or lending survey data from macro-financial and bank-specific factors. Instead, I use bank-individual leverage ratios, defined as total assets over equity, as leverage has been found to be the main indicator of a bank's ability to grant credit (Adrian and Shin, 2010) and as the bank leverage cycle is a main determinant of cross-border transmission of financial conditions via capital flows (Bruno and Shin, 2015b). Moreover, a bank's leverage is closely related to a simple Value-at-Risk (VaR) rule that targets a constant probability of default and implies that banks increase their leverage by exploiting any changes in prices and decreases in measured risk during upswings, and deleverage during downturns when markets come under stress, thereby actually amplifying the downturn (Adrian and Shin, 2014).

Third, from a methodological point of view the paper is the first that applies the external instrument identification method (Stock and Watson, 2012, Mertens and Ravn, 2013) to GVAR models. Many recent contributions applying GVAR models use sign restrictions to identify structural shocks with the majority of macroeconomic works either studying shocks originating in the U.S. (Eickmeier and Ng, 2015, Feldkircher and Huber, 2016, Georgiadis, 2016, Anaya et al., 2017, among others) or investigating effects of shocks related to the eurozone on individual euro area member countries (Georgiadis, 2015, Gross et al., 2016, 2017). The validity of the approach requires that the instrument is informative (relevance condition) and second that it is contemporaneously exogenous to factors not only of the country/region of origin of the shock, but also of other countries included in the GVAR model (exogeneity condition). This assumption seems satisfied if shocks are considered that originate from large economies like the U.S. or the euro area (cf. Cesa-Bianchi et al., 2018) and hence is applicable to many GVAR analyses.

The results suggest that European bank balance sheet shocks significantly affect gross capital inflows and real credit growth in countries across different geographical regions, but have only minor effects on real output growth in the majority of countries and geographical regions. In comparison to typical sign-restricted credit supply shocks (Eickmeier and Ng, 2011, Fadejeva et al., 2015), bank balance sheet shocks have weaker effects on credit and especially on real output since banks can change their leverage ratio in various ways with a different impact on credit supply to the non-financial private sector and on real economic activity (Gross et al., 2016). Looking at aggregated country groups, advanced economies which are financially developed and open are generally more affected than emerging market economies with less developed and less open financial markets. In contrast, the sheer number of European banks present in a country seems to be of subordinate importance. These results are robust to a range of sensitivity analyses regarding both, the construction of the instrument and the specification of the GVAR model.

The remainder of the chapter is structured as follows. The next section provides an overview of the related literature with a focus on the global financial cycle and its drivers as well as on the role of European banks in the global financial system. The subsequent section elaborates on the construction of the external instrument, while Section 4.4 discusses the GVAR model, the approach of identification via external instruments as well as the data and specification of the GVAR model. Section 4.5 presents the main results and outlines some robustness checks, while the last section concludes.

4.2 Related Literature

The paper is primarily related to two strands of the literature, namely to works on drivers of cross-border capital flows and transmission channels of financial conditions and second to contributions on the role of European banks in the global financial system. The first strand is based on the observation that financial conditions in advanced and emerging economies have become more interrelated in recent decades, a phenomenon known as the “global financial cycle”

(Rey, 2013). The global financial cycle is reflected in an increasing global co-movement of asset prices, credit growth, and gross capital flows across economies regardless of the specific exchange rate regime in place (Rey, 2013, Passari and Rey, 2015), with a considerable share of the variance explained by a common global factor (Miranda-Agrippino and Rey, 2018).

The existence of the global financial cycle raises the question of its determinants and is associated with the notion of global "push" factors in driving cross-border capital flows.[2] Forbes and Warnock (2012) and Fratzscher (2012) identify common push factors like global risk as significant determinants of capital flows, while country-specific characteristics tend to be of subordinate relevance regardless of non-negligible country heterogeneity. A main driver of the global financial cycle is U.S. monetary policy which has a strong impact on cross-border credit flows, worldwide credit growth, and the leverage of global banks (Rey, 2013, Miranda-Agrippino and Rey, 2018), and also affects financial conditions in inflation targeting countries with freely floating exchange rates (Passari and Rey, 2015, Rey, 2016).[3] Furthermore, there is evidence that U.S. monetary policy influences global investor risk as measured by the VIX (Bekaert et al., 2013, Bruno and Shin, 2015a, Passari and Rey, 2015), which is itself considered to be a main determinant of global liquidity and banks' leverage (Rey, 2013, Bruno and Shin, 2015b).

While global financial institutions transmit financial conditions by reacting to U.S. monetary policy (Bruno and Shin, 2015a, Miranda-Agrippino and Rey, 2018), they also affect global financial conditions directly by passing on balance sheet shocks through the provision of cross-border credit. Many important contributions provide empirical evidence that international transmission of bank balance sheet shocks lead to a reduction in lending not only in the bank's home country, but also in foreign countries where it is active (Cetorelli and Goldberg, 2011, 2012, Schnabl, 2012, among others).[4] Giannetti and Laeven (2012a) find that banks decrease the share of foreign loans in their portfolio during periods of financial turmoil ("flight home effect", see also Giannetti and Laeven, 2012b)[5], while they increase it during times of favorable funding conditions ("flight abroad effect"). Shin (2012) concludes that the (de-)leveraging cycle of global banks is the main driver underlying global liquidity and the transmission of associated credit conditions, and Bruno and Shin (2015b) present a model of the international banking system that predicts a crucial role for the leverage cycle of global banks in transmitting financial conditions. The

[2] The distinction between global "push" factors and country-specific "pull" factors dates back to the work of Calvo et al. (1996), who pointed towards the role of the U.S. interest rate as an important "push" factor.

[3] Chen et al. (2016), Anaya et al. (2017), Dedola et al. (2017), and Fratzscher et al. (2018) among others analyze the international transmission and impact of U.S. monetary policy on advanced and emerging market economies as well as its effect on cross-border capital flows.

[4] Specifically, bank balance sheet shocks in industrialized countries during the global financial crisis led to a significant reduction in loan supply in emerging market economies (Cetorelli and Goldberg, 2011) and forced foreign bank branches in the U.S. to cut their lending (Cetorelli and Goldberg, 2012). Likewise, the 1998 Russian default caused a reduction in lending by international banks to Peruvian banks, who then themselves curtailed their lending to Peruvian firms (Schnabl, 2012).

[5] De Haas and Lelyveld (2014) document that subsidiaries of multinational banks curtailed credit growth almost three times as much as domestic banks during the global financial crisis. The reduction in cross-border lending was relatively less in geographically close countries, where the bank operated a local subsidiary, was part of a network with domestic co-lenders, or had gained pre-crisis lending experience (De Haas and Horen, 2013).

bank leverage cycle is driven by fluctuations in collateral requirements ("haircuts") as well as by exchange rate movements. Cesa-Bianchi et al. (2018) use innovations to the leverage of U.S. security broker-dealers as a proxy for identifying international credit supply shocks in a panel VAR model and find that they explain twice as much of the variation in, inter alia, cross-border credit, house prices, and consumption as a U.S. monetary policy shock.

Interestingly, it appears that global European banks are of crucial importance for the global financial system in recent decades and only less so U.S. investment banks. In contrast to U.S. bank conditions, Cerutti et al. (2017) find that European bank conditions matter for cross-border bank flows on top of traditionally documented factors like the U.S. monetary policy stance, U.S. exchange rate dynamics and investor uncertainty (VIX). In fact, prior to the global financial crisis euro area and U.K. banks have provided more cross-border credit than U.S. banks (Cerutti et al., 2017) and a large part of cross-border lending by European banks was denominated in U.S. dollars (Baba et al., 2009, Shin, 2012).[6] Likely reasons for this rise in cross-border lending are a combination of lax regulation and - with respect to euro area banks - the introduction and subsequent appreciation of the euro vis-á-vis other major currencies (Noeth and Sengupta, 2012, Shin, 2012, Bruno and Shin, 2015b, Avdjiev et al., 2016). The substantial increase in U.S. dollar denominated asset holdings of European banks led to the build-up of considerable funding risk which was rooted in a mismatch between unstable short-term U.S. dollar funding, mainly from U.S. money-market funds, and long-term U.S. dollar lending to non-banks (McGuire and von Peter, 2009, Shin, 2012, Ivashina et al., 2015).[7] When the funding sources froze during the global financial crisis and the sovereign debt crisis in the eurozone, this mismatch forced European banks to cut their U.S. dollar lending. Acharya et al. (2017) demonstrate that non-U.S. banks active in the U.S. asset-backed commercial paper market had problems to fund U.S. dollars when the market froze in August 2007. Ivashina et al. (2015) show how eurozone banks cut back their U.S. dollar lending relative to their euro-denominated lending during the euro area sovereign debt crisis. Their deteriorating creditworthiness prompted U.S. money market funds to curtail the supply of U.S. dollars to them. Correa et al. (2016) provide additional evidence that this funding shock forced U.S. branches of euro area banks to cut their lending to U.S. firms, who then had to reduce their investments. In sum, Shin (2012) concludes that deleveraging of European global banks bears substantial consequences for credit supply in and capital flows to advanced and emerging economies, especially with regards to the United States. Moreover,

[6] Specifically, Shin (2012) shows that in the years prior to the global financial crisis European banks had enormous U.S. dollar claims against U.S. counterparties (of around $5 trillion), but also against other advanced and emerging economies. Furthermore, Ivashina et al. (2015) document that European banks accounted for approximately 28% of the U.S. syndicated loan market over the period 2005-2007.

[7] With respect to funding, Baba et al. (2009) document that by mid-2008 around 50% of assets of U.S. prime money market funds were short-term obligations of foreign banks, with European banks representing the vast majority. On the asset side, European banks were mainly lending indirectly to U.S. borrowers through the shadow banking system by purchasing mortgage-backed securities and several other structured securities (Shin, 2012). Acharya and Schnabl (2010) report that European banks sponsored the vast majority of U.S. dollar-denominated asset-backed commercial paper vehicles, while U.S. banks accounted for just around 30%.

Feyen and del Mazo (2013) point out that European banks have a dominant role in specialized finance areas like project or trade finance that cannot be easily offered by other banks.

However, most existing works analyze the effects of bank capital shocks in the eurozone or Europe, but do not investigate spillovers to other regions. Closely related in this regard are Gross et al. (2016) and Gross et al. (2017) who study how deleveraging through its impact on credit supply affects business cycle dynamics within a mixed-cross-section global VAR model for European countries and banking systems. The authors distinguish between three different types of leverage shocks and conclude that the real economy is affected adversely only when banks deleverage by shrinking their balance sheets. Further contributions include Kanngiesser et al. (2017) who find that euro area banks raise their capital ratios by reducing their lending comparatively more than increasing their level of capital; Altavilla et al. (2015) who construct a loan supply indicator and employ it to identify a credit supply shock in the eurozone; and Peersman (2012) who investigates different types of euro area bank lending shocks. In contrast to these works, this chapter analyzes the global spillovers of shocks to the balance sheet of large European banks identified by means of an external instrument on gross capital inflows and real credit growth in a global VAR model with 30 advanced and emerging economies.[8]

4.3 A Proxy for an European Bank Balance Sheet Shock

The literature suggests that (de-)leveraging by European banks plays a crucial role for global liquidity and credit supply. In the following, I describe how to construct a proxy for (de-)leveraging by large, globally active European banks that can be used to identify balance sheet shocks within a time series framework by applying the identification method via external instruments.

The idea and methodological approach for deriving a measure proxying bank balance sheet shocks that is exogenous of macro-financial conditions and bank-specific factors is based on previous work. Specifically, Hancock and Wilcox (1993, 1994) propose a partial adjustment model between actual and target bank capital, with the latter modeled as a linear function of bank-specific, institutional and macroeconomic control variables. The estimated gap between the actual and target capital ratio yields a measure of capital surplus/shortfall per period, which can then be used to gauge the effect on loan supply (Berrospide and Edge, 2010) or be aggregated into a measure of exogenous shocks to capital ratios (Mésonnier and Stevanovic, 2012). Similarly, Bassett et al. (2014) and Altavilla et al. (2015) partial out macro-financial and bank-specific factors from survey data on bank lending and utilize the estimated residuals to derive an exogenous measure on bank lending shocks.[9] In contrast to these papers, I employ bank-individual lever-

[8] Eickmeier and Ng (2011), which is an earlier discussion paper version of Eickmeier and Ng (2015), and Fadejeva et al. (2015) study euro area credit supply shocks in a GVAR model. Note, however, that these shocks are identified by sign restrictions on outstanding credit and hence are different from bank balance sheet shocks with a priori ambiguous response of credit (Gross et al., 2016), let alone differences in the GVAR model specification.

[9] Bassett et al. (2014) apply survey data from the "Senior Loan Officer Opinion Survey on Bank Lending Practices" (SLOOS) by the U.S. Federal Reserve Bank and include the measure as an endogenous variables in a VAR model for the U.S., while Altavilla et al. (2015) use a loan supply indicator based on the ECB's "Bank Lending Survey" (BLS) as an external instrument in a VAR model for the aggregate eurozone.

age ratios, defined as total assets over equity, and regress them on a set of macro-financial and bank-individual control variables in a panel setting. The choice for a simple leverage measure instead of a bank capital ratio is motivated by findings that leverage is the main indicator of a bank's ability to grant credit (Adrian and Shin, 2010) and that the bank leverage cycle is a main determinant of cross-border transmission of financial conditions via capital flows (Bruno and Shin, 2015b). Moreover, leverage of U.S. security broker and dealers (Adrian and Shin, 2010) and large European banks (Kalemli-Ozcan et al., 2012) is procyclical, meaning that total assets and leverage grow in lockstep, with equity being the exogenous variable.[10] This observed procycality of leverage can be explained by a simple Value-at-Risk (VaR) rule according to which financial intermediaries target a constant probability of default, implying that they adjust their exposures continuously to keep a fixed ratio of VaR to equity, while the VaR per dollar of assets varies considerably (Adrian and Shin, 2014). In essence, this means that financial intermediaries operating under a VaR rule leverage by exploiting any changes in prices and decreases in measured risk during upswings, and deleverage during downturns when markets come under stress, thereby actually amplifying the downturn.[11] Partialling out factors like business cycle and global financial conditions, the monetary policy stance or bank-specific characteristics that affect a bank's VaR rule and hence leverage allows deriving an exogenous measure of supply-side shifts in a bank's leverage. This measure can then be applied as a proxy for an exogenous balance sheet shock in a time series framework, identified by means of the external instrument method.

Note that, while a balance sheet shock identified in this way is related to a bank's ability to grant credit, there are several ways for banks to adjust their leverage ratio and to achieve their target VaR, either via the asset or the liability side.[12] In contrast to Gross et al. (2016) who identify three different type of shocks with sign restrictions on the outstanding loan volume (expansionary, contractionary, and an unconstrained one), my approach does not require to impose any sign restrictions and yields the actual average effect. In any case, it is important to be aware of the difference to a single sign-restricted standard credit supply shock as analyzed in a GVAR context by Eickmeier and Ng (2011, 2015) and Fadejeva et al. (2015). Intuitively, the identified shock can be interpreted in two ways, both affecting a bank's VaR rule and hence its leverage, as well as potentially, but not necessarily, its supply of credit. First, it could capture a bank's ability to raise funding in the market. For instance, prior to the global financial crisis liquidity was abundant and collateral requirements low, allowing European banks to expand their

[10] This is in contrast to U.S. commercial banks, non-financial firms, and households (Adrian and Shin, 2010) as well as to small European banks (Kalemli-Ozcan et al., 2012).

[11] This latter effect is illustrated by the "margin spiral" of Brunnermeier and Pedersen (2009), where an initial funding shock lowers market liquidity and leads to higher haircuts. Higher margins tighten the funding constraints of financial intermediaries who have to adjust their leverage by either raising new equity or by disposing of assets. This further reduces market liquidity and spills over to other intermediaries, sowing the seeds of a margin spiral. See also Geanakoplos (2010) for a theoretical examination of the leverage cycle.

[12] In detail, it can reduce its assets and hence balance sheet size by selling off business lines, divesting liquid assets, and reducing lending by not renewing maturing loans. Second, it can raise equity capital and invest it in new assets, thereby actually expanding its balance sheet. Third, it can raise equity and replace debt, leaving the size of its balance sheet unaffected. (Gross et al., 2016)

balance sheets substantially. In contrast, during and in the aftermath of both, the global financial crisis and the sovereign debt crisis in the euro area, liquidity squeezed, haircuts increased and European banks faced considerable funding difficulties. Second, one can also think of changes in a bank's risk assessment, either due to alterations in its own perception of risk and monitoring incentives or due to regulatory requirements. For example, prior to the financial crisis financial innovation led to the creation of various forms of structured securities like asset/mortgage backed securities or collateralized debt obligations that allowed banks to off-load credit risk[13], while in the aftermath many regulations like minimum capital requirements were tightened or newly introduced, forcing banks to adjust their exposures. Supporting narrative evidence for these shock interpretations comes from a survey among European banks conducted by Deloitte (2012) in which the five most frequent named drivers of deleveraging are higher capital requirements, higher liquidity requirements, EU state aid requirements, a change in strategy and increased cost of funding/funding constraints.[14]

The panel model applied to obtain the exogenous measure proxying the balance sheet shock is at quarterly frequency and encompasses the period 1999Q1-2016Q4. While being unbalanced, the panel consists in total of 33 large European global banks. A list of all banks in the sample, including the quarter of the first observation, is provided in Table 4.3 in Appendix 4.A. The decision to consider only large European global banks follows Cerutti et al. (2017) and is driven by the fact that these banks engage substantially in cross-border lending and are more reliant on market-based funding. Thus, their leverage seems to be better suited to capture European banks' funding conditions and risk attitudes, and their lending decision might affect borrowers abroad Europe as well. Specifically, I run the following dynamic fixed effects panel regression:

$$LEV_{i,t} = \alpha + \beta LEV_{i,t-1} + \boldsymbol{\gamma}'\mathbf{x}_{(j),t-1} + \boldsymbol{\delta}'\boldsymbol{\omega}_{i,t-1} + \eta_i + \nu_{i,t}, \tag{4.1}$$

where $LEV_{i,t}$ is the leverage ratio[15], defined as total assets over equity, of bank i in quarter t, $\mathbf{x}_{(j),t} = [\mathbf{x}'_{j,t}, \mathbf{x}'_{\bullet,t}]'$ is a vector of indicators capturing macroeconomic and financial conditions which are either specific to country j ($\mathbf{x}_{j,t}$) or are of global nature ($\mathbf{x}_{\bullet,t}$), $\boldsymbol{\omega}_{i,t}$ is a vector of bank-specific controls, α is a constant, β a coefficient, $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$ coefficient vectors, η_i denotes the bank fixed effect of bank i, and $\nu_{i,t}$ the residual.

The lagged leverage ratio takes into account that during non-crisis times leverage ratios tend to be quite persistent with only gradual changes from quarter to quarter. The matrix $\mathbf{x}_{(j),t}$ includes several indicators that are aimed to capture macroeconomic and financial conditions which likely affect the leverage of European banks and might be demand-driven. On a country level, real GDP growth and the unemployment rate control for the current state of the domestic economy and hence for the demand for credit by the non-financial private sector, while the credit-to-GDP

[13] This might be accompanied by ambiguity attitudes and endogenous beliefs formation that lead to waves of borrowers' optimism during booms and pessimism during downturns. (Bassanin et al., 2018)

[14] In contrast, reduced demand for credit/weaker economic activity was named by less than 10% of banks.

[15] Extreme outliers of leverage ratios, especially during crisis times, have been excluded from the sample. See the description below Table 4.3 in Appendix 4.A for detailed information.

ratio indicates phases of credit booms and crunches, respectively. In addition, several measures of global and euro area financial conditions are taken into account, namely the Eonia rate, the federal funds rate, the VSTOXX, the Excess Bond Premium (Gilchrist and Zakrajšek, 2012b), the nominal U.S. Dollar/Euro exchange rate, and the leverage of U.S. security broker-dealers. Specifically, U.S. monetary policy has been found to affect the leverage of global European banks (Bruno and Shin, 2015a, Miranda-Agrippino and Rey, 2018). The exchange rate of the U.S. dollar with respect to the Euro is intended to reflect the dominant position of the U.S. dollar as a global funding currency (Ivashina et al., 2015) and hence its relevance for global liquidity (Bruno and Shin, 2015b, McCauley et al., 2015, Avdjiev et al., 2016) and further accounts for the appreciation of the euro against the U.S. dollar prior to the financial crisis. The European VSTOXX[16] and the Excess Bond Premium (Gilchrist and Zakrajšek, 2012b) are supposed to measure the risk-bearing capacity of European banks, while the leverage of U.S. security broker-dealers controls for international credit supply shocks originating from U.S. global banks (Cesa-Bianchi et al., 2018).[17]

The bank-specific factors collected in $\boldsymbol{\omega}_{i,t}$ like size, profitability and balance sheet composition potentially not only affect the level of leverage directly, but likely also respond to other macroeconomic shocks that in turn affect demand for credit and the leverage of banks (Berrospide and Edge, 2010, Mésonnier and Stevanovic, 2012, Bassett et al., 2014).[18] Specifically, I measure the size of a bank by its total assets as larger banks have been found to be more leveraged (Laeven et al., 2016), and a bank's profitability by its return-on-assets (ROA), a control variable frequently included in works about the determinants of bank capital ratios (Ayuso et al., 2004, Heid et al., 2004, Gropp and Heider, 2010, Brei and Gambacorta, 2016). Further, the return of a bank's stock influences its ability to raise additional capital and thus affects its leverage (Bassett et al., 2014), while a bank's charter value, as proxied by Tobin's q (Bassett et al., 2014), acts as a self-disciplinary mechanism in that banks with a higher charter value face lower leverage and default risk (Keeley, 1990, Demsetz et al., 1996, Gropp and Vesala, 2004, Furlong and Kwan, 2006). A bank's liquidity position is captured first by the share of deposits to assets which provides an insight on a bank's overall liquidity position and sensitivity to financial shocks (Bassett et al., 2014) and second by the loans-to-deposits ratio that relates the part of relatively illiquid assets of a bank to its stable funding. Finally, the panel regression features a bank-specific fixed effect that is supposed to control for any unobserved determinants of leverage like for example regulatory measures.[19] A list of all variables together with the data source and their treatment,

[16] Note that the VIX is included in the GVAR model later which is why here the VSTOXX is applied.

[17] These variables pretty much match with determinants of net flows of eurozone banks vis-á-vis extra-euro residents as found by Everett (2016).

[18] Everett (2016) reveals some heterogeneity in the sensibility of cross-border flows of euro area banks to global liquidity with respect to, inter alia, bank size, bank capitalization and the share of deposit funding.

[19] As there are many countries with just one bank in the sample I abstain from including country-fixed effects in addition. Further note that following Bassett et al. (2014) there are no time fixed effects since this would absorb most of the fundamentally unexplained leverage movements and thus would produce an uninformed instrument that cannot be applied to identify the shock in the GVAR model below.

including a note on dealing with outliers, summary statistics and correlations are provided in Tables 4.4 to 4.6, respectively, in Appendix 4.A.

Table 4.1 displays the results for different variants of the panel regression given in Equation (4.1). The first specification just includes the lagged leverage value, in the second macroeconomic and financial indicators are added and the third also contains bank-specific controls on top. These first three variants are estimated by a two-step system GMM estimator, while the last two columns report for comparison estimation results of the full specification using a cross-sectional time-series FGLS estimator featuring heteroskedastic errors that follow an individual AR(1) process and an OLS fixed effects estimator with AR(1) disturbances.[20] Starting with the first specification, one sees that as expected the lagged leverage value is highly significant, but that this simple dynamic system is not stable given an estimate larger than unity. When macro-financial controls are added to the panel regression, the estimate of the lagged leverage value drops below unity but remains highly significant. Among the additional variables, five turn out to be significant: real GDP growth, the credit-to-GDP ratio and the EONIA rate are positively related to a bank's leverage level, while the point estimates of the federal funds rate and the VSTOXX feature a negative sign. Worth mentioning is the opposite sign of the two short-term interest rates: while the negative relation of the federal funds rate to the leverage of European banks squares with previous findings according to which easy U.S. monetary policy is a driver of global liquidity and leverage of financial institutions (Bruno and Shin, 2015a, Miranda-Agrippino and Rey, 2018)[21], the positive effect of the EONIA rate on leverage seems to be counterintuitive and might only be technically explained as changes in the EONIA rate were lagging changes in the federal funds rate for most parts of the sample period. The full specification takes into account the bank-individual factors as well. Note that all previously found significant variables but the credit-to-GDP ratio keep their significance with only minor quantitative changes in most cases. Of the bank-individual factors, the ROA (at the 5% level, with a positive sign), Tobin's q (at the 5% level, with a negative sign) and the deposit-to-assets ratio (at the 10% level, with a negative sign) are significant determinants of the leverage of European banks. The last two columns of the table compare these results to estimates obtained when applying the different estimators. As both alternative estimators are biased, it comes as no surprise that there are quantitative differences. Nonetheless, most variables keep their significance, even though the simple FE estimator produces somewhat different results.

The main purpose of the panel regression lies in utilizing the residuals to create the instrument used to identify the shock of interest in the GVAR model below. Specifically, in the baseline version I aggregate the bank-specific residuals stemming from the GMM estimation of the full

[20] Judson and Owen (1999) suggest that the well-known bias when using OLS in estimating a dynamic panel with fixed effects goes quickly to zero given the time dimension is more than 30. Although the full sample period in my case encompasses 72 quarters, I prefer the GMM estimator as the average (median) bank is 41 (45) periods in the sample, with some banks being present less than 30 periods.

[21] Relatedly, McCauley et al. (2015) document that levels of the effective federal funds rate below that implied by the Taylor rule are associated with a higher growth of loans denominated in U.S. dollars to non-U.S. borrowers.

Table 4.1: Results from the Panel Regression

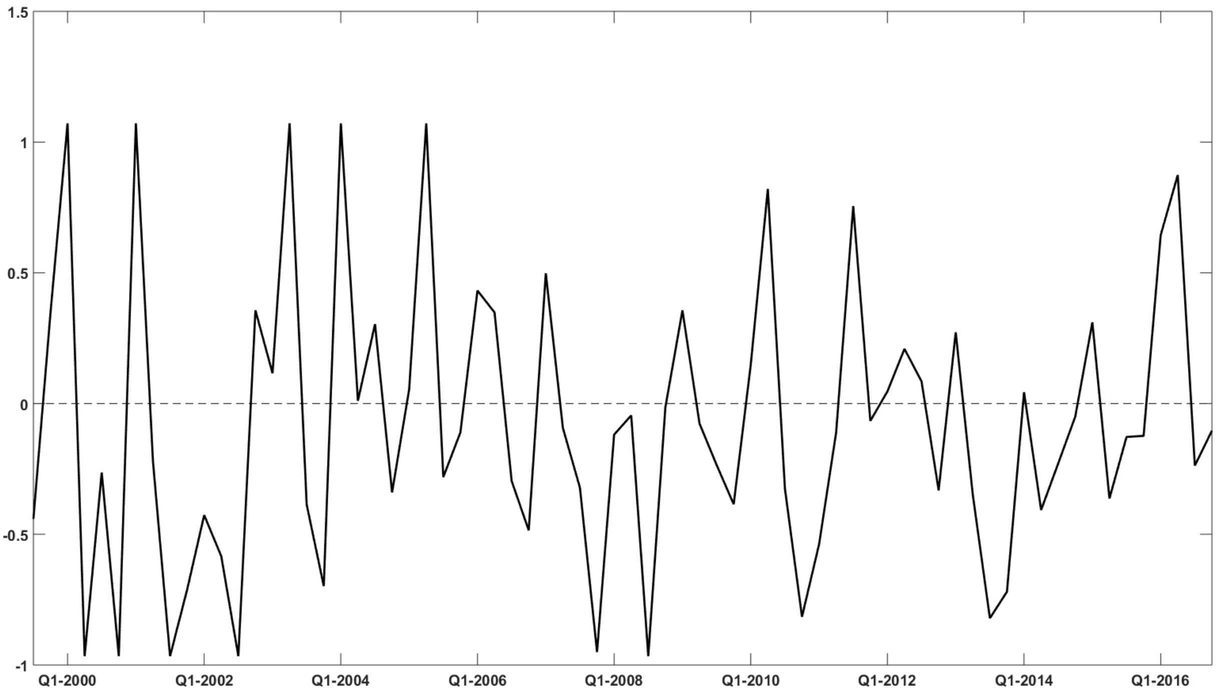
Dependent variable: leverage defined as total assets over equity					
Variable	*Two-Step System GMM*			*FGLS*	*FE AR(1)*
Leverage$_{t-1}$	1.0192*** (0.0099)	0.9629*** (0.0145)	0.9457*** (0.0250)	0.9541*** (0.0079)	0.8895*** (0.0142)
ΔReal GDP$_{t-1}$		0.3198*** (0.0909)	0.3448** (0.1305)	0.2100*** (0.0625)	0.3870*** (0.0969)
Unemployment Rate$_{t-1}$		0.0057 (0.0073)	0.0090 (0.0147)	0.0016 (0.0085)	0.0764*** (0.0266)
Credit/GDP$_{t-1}$		0.0025* (0.0013)	0.0032 (0.0021)	0.0025 (0.0016)	0.0033 (0.0049)
Eonia Rate$_{t-1}$		0.5199*** (0.1127)	0.5878*** (0.1458)	0.2977*** (0.0772)	0.6338*** (0.1313)
Federal Funds Rate$_{t-1}$		−0.1853*** (0.0546)	−0.1759*** (0.0501)	−0.1193*** (0.0450)	−0.2069*** (0.0726)
VSTOXX$_{t-1}$		−0.0311*** (0.0096)	−0.0292*** (0.0080)	−0.0179** (0.0072)	−0.0271** (0.0117)
EBP$_{t-1}$		−0.0169 (0.0773)	−0.0158 (0.0811)	0.0689 (0.0975)	−0.0036 (0.1557)
FX USD/EUR$_{t-1}$		0.5781 (0.4052)	0.1809 (0.5066)	0.1338 (0.3557)	0.0103 (0.6342)
U.S. broker-dealers leverage$_{t-1}$		−0.0315 (0.0270)	−0.0298 (0.0320)	−0.0093 (0.0172)	0.0018 (0.0281)
ln(Assets)$_{t-1}$			0.0034 (0.1161)	−0.0319 (0.0521)	−0.0881 (0.2441)
ROA$_{t-1}$			0.3258** (0.1362)	0.2260** (0.1001)	0.2369 (0.1921)
Tobin's q_{t-1}			−9.7520** (3.7781)	−4.7755*** (1.5014)	−7.0876** (3.3272)
ΔStock$_{t-1}$			0.0014 (0.0025)	−0.0007 (0.0021)	0.0003 (0.0035)
Deposits/Assets$_{t-1}$			−0.0227* (0.0130)	−0.0179*** (0.0068)	−0.0485*** (0.0171)
Loans/Deposits$_{t-1}$			−0.0034 (0.0031)	−0.0017 (0.0013)	−0.0062* (0.0032)
Constant	y	y	y	y	y
Bank FE	y	y	y	y	y
Time FE	n	n	n	n	n
Observations	1667	1667	1323	1323	1291
No. of Banks	33	33	32	32	32

Note: The table reports the estimated coefficients along with robust standard errors (in parentheses) of the dynamic panel regression. Columns 2 to 4 show for different model specifications the estimates using a two-step system GMM estimator featuring forward orthogonal deviations. Column 5 and 6 display the estimates for the full model specification using a cross-sectional time-series FGLS estimator featuring heteroskedastic errors that follow an individual AR(1) process and a FE panel estimator with an AR(1) error term, respectively. Note that the last two estimators are potentially biased in this dynamic setting, but are reported for the sake of comparison as they have beneficial features in the $N < T$ context. The panel consists of 33 (32) large European banks and encompasses the time period from 1999Q1 to 2016Q4, but is unbalanced. All specifications include bank fixed effects (not reported). ***, **, * indicate significance at the 1%, 5%, and 10% level, respectively. See Table 4.3 in Appendix 4.A for the list of included banks and their time coverage.

specification version that controls for macroeconomic, financial, and bank-specific factors to one time-series measure by taking the quarterly median value. As the panel is unbalanced, the median is least biased by banks entering/leaving the sample (as would be the case when aggregating by use of weights based on a bank's size) and more robust to outliers (in contrast to the mean). In a final step I winsorize the instrument at the 5% and 95% level, respectively, to control for extreme outliers (cf. Piffer and Podstawski, forthcoming) that might drive the effects of the identified shock in the GVAR model. To check the sensitivity of the results in the GVAR model to these choices, I employ the instruments derived from the two alternative estimators, the two alternative aggregation methods as well as the unwinsorized instrument in robustness checks.

Figure 4.1 shows the resulting time series of shifts in the leverage ratio of large European banks that cannot be explained by the set of controls included in the panel regression. The time series matches well with anecdotal evidence about the leverage dynamics of European banks in the two recent decades. Positive values indicate that leverage was on average larger than predicted by the included macro-financial and bank-specific control factors, while in case of negative values the opposite is true. Put differently, positive values imply phases of over-leveraging and negative values of under-leveraging. For instance, we see that after the bursting of the dot-com bubble at the beginning of the sample, during the global financial crisis and in the aftermath of the sovereign debt crisis in the eurozone, large European banks were deleveraging by more than predicted by the controls. In contrast, in the years prior to the financial crisis a series of large positive values indicates that European banks were increasing their leverage by more than is explained by fundamentals. This time series constitutes the proxy, that is, the external instrument that is used to identify the balance sheet shock in the GVAR model.

Figure 4.1: Instrument Based on Unexplained Shifts in the Leverage of Large European Banks



Note: The figure shows the time series of shifts in the leverage ratio of large European banks that is unexplained by the macro-financial and bank-specific factors included in the full specification of the panel regression given in Equation (4.1), applying a two-step system GMM estimator. Aggregation is performed by taking the median of the bank-individual residuals per quarter. The time series serves as a proxy, that is, as the external instrument, for identifying the balance sheet shock in the GVAR model below.

4.4 Methodological Framework

This section first discusses the global VAR (GVAR) model and then outlines how the instrument constructed in the previous section can be utilized to identify the structural shock to the balance sheet of large European banks in the GVAR model. Subsequently, the data and the specification of the GVAR model are described.

4.4.1 The Global VAR Model

Ideally, domestic and international spillover effects of European bank balance sheet shocks would be analyzed by means of a large scale VAR model which takes all potential cross-country inter-linkages into account. As is well known, estimation of such a model under a fully flexible parameterization is infeasible. This paper employs the GVAR approach pioneered by Pesaran et al. (2004) and Dees et al. (2007) to solve the dimensionality problem in a theoretically consistent way as it is easily applicable and interpretable.[22]

In its essence, a GVAR model is a set of linked small-scale country specific conditional models that are estimated separately in a first step. Each individual country $j = 1, \ldots, N$ model consists of domestic endogenous variables and country-specific exogenous cross-section averages of foreign variables and thus is a VARX model given by:

$$\mathbf{y}_{j,t} = \sum_{\ell=1}^{p_j} \mathbf{A}_{j,\ell}\mathbf{y}_{j,t-\ell} + \sum_{\ell=0}^{q_j} \mathbf{B}_{j,\ell}\mathbf{y}^*_{j,t-\ell} + \sum_{\ell=0}^{r} \mathbf{C}_{j,\ell}\mathbf{d}_{t-\ell} + \boldsymbol{\lambda}_j t + \boldsymbol{\mu}_j + \mathbf{u}_{j,t}, \tag{4.2}$$

where $\mathbf{y}_{j,t}$ represents the $k_j \times 1$ vector of domestic endogenous variables, $\mathbf{y}^*_{j,t}$ is the $k^*_j \times 1$ vector of country-specific foreign variables, $\mathbf{d}_t$ denotes a $k_d \times 1$ vector of global variables stemming from the dominant unit model defined below, t is a linear trend and $\boldsymbol{\mu}_j$ a constant, and $\mathbf{u}_{j,t}$ the $k_j \times 1$ vector of serially uncorrelated errors with $\mathbf{u}_{j,t} \sim \text{IID}(0, \Sigma_{uj})$. $\mathbf{A}_{j,\ell}$, $\mathbf{B}_{j,\ell}$, $\mathbf{C}_{j,\ell}$ are coefficient matrices and $\boldsymbol{\lambda}_j$ a coefficient vector which are all of suitable dimensions.

The key feature in the GVAR solution to the curse of dimensionality is defining the foreign variables as weighted averages of other countries' variables with bilateral weights w_{js}:

$$\mathbf{y}^*_{j,t} = \sum_{s=1}^{N} w_{js}\mathbf{y}_{j,t}, \qquad \sum_{s=1}^{N} w_{js} = 1, \qquad w_{js} \geq 0 \;\forall\; j, s, \qquad w_{jj} = 0.$$

The weights capture the exposure of country j to country s, which are typically based on bilateral trade linkages or capital flows. For estimation purposes, the foreign variables $\mathbf{y}^*_{j,t}$ are assumed to be weakly exogenous with respect to the parameters of the VARX model in Equation (4.2); an assumption which seems admissible given that N is 30 in this model.

[22] Moreover, GVAR models are well established as witnessed by a large number of papers applying them; see for instance Chudik and Fratzscher (2011), Fadejeva et al. (2015), Crespo Cuaresma et al. (2015), Eickmeier and Ng (2015), Georgiadis (2015, 2016), Chen et al. (2016), Feldkircher and Huber (2016), and Anaya et al. (2017).

Pooling deterministics together with the corresponding coefficients in the vector $\boldsymbol{h}_{j,t} = \boldsymbol{\lambda}_j t + \boldsymbol{\mu}_j$, Equation (4.2) can be rewritten as

$$\boldsymbol{\Phi}_{j,0}\mathbf{z}_{j,t} = \sum_{\ell=1}^{p} \boldsymbol{\Phi}_{j,\ell}\mathbf{z}_{j,t-\ell} + \sum_{\ell=0}^{r} \mathbf{C}_{j,\ell}\mathbf{d}_{t-\ell} + \mathbf{h}_{j,t} + \mathbf{u}_{j,t}, \tag{4.3}$$

where $\mathbf{z}_{j,t} = (\mathbf{y}'_{j,t}, \mathbf{y}^{*\prime}_{j,t})'$, $\boldsymbol{\Phi}_{j,0} = (\mathbf{I}_k, -\mathbf{B}_{j,0})$, $\boldsymbol{\Phi}_{j,\ell} = (\mathbf{A}_{j,\ell}, \mathbf{B}_{j,\ell})$, and $p = \max_j(p_j, q_j)$. $\mathbf{z}_{j,t}$ is then linked to the endogenous variables $\mathbf{y}_t = (\mathbf{y}'_{1,t}\ \mathbf{y}'_{2,t} \dots, \mathbf{y}'_{N,t})'$ via the link matrix $\mathbf{W}_j$ in the following way

$$\mathbf{z}_{j,t} = \mathbf{W}_j\mathbf{y}_t, \qquad \mathbf{W}_j = \begin{pmatrix} \mathbf{0} & \cdots & \mathbf{I}_{k_j} & \cdots & \mathbf{0} \\ w_{j,1}\mathbf{I}_{k_j^*} & \cdots & w_{j,j}\mathbf{I}_{k_j^*} & \cdots & w_{j,N}\mathbf{I}_{k_j^*} \end{pmatrix}$$

where $\mathbf{W}_j$ is of dimension $(k_j + k_j^*) \times k$ with $k = \sum_{j=1}^{N} k_j$. Using this relation, Equation (4.3) is equivalent to

$$\boldsymbol{\Phi}_{j,0}\mathbf{W}_j\mathbf{y}_t = \sum_{\ell=1}^{p} \boldsymbol{\Phi}_{j,\ell}\mathbf{W}_j\mathbf{y}_{t-\ell} + \sum_{\ell=0}^{r} \mathbf{C}_{j,\ell}\mathbf{d}_{t-\ell} + \mathbf{h}_{j,t} + \mathbf{u}_{j,t}. \tag{4.4}$$

The individual country VARX models are then stacked to obtain the model for all the variables in the global model:

$$\mathbf{G}_0\mathbf{y}_t = \sum_{\ell=1}^{p} \mathbf{G}_\ell\mathbf{y}_{t-\ell} + \sum_{\ell=0}^{r} \mathbf{C}_\ell\mathbf{d}_{t-\ell} + \mathbf{h}_t + \mathbf{u}_t, \tag{4.5}$$

where

$$\mathbf{G}_0 = \begin{pmatrix} \boldsymbol{\Phi}_{1,0}\mathbf{W}_1 \\ \boldsymbol{\Phi}_{2,0}\mathbf{W}_2 \\ \vdots \\ \boldsymbol{\Phi}_{N,0}\mathbf{W}_N \end{pmatrix}, \mathbf{G}_\ell = \begin{pmatrix} \boldsymbol{\Phi}_{1,\ell}\mathbf{W}_1 \\ \boldsymbol{\Phi}_{2,\ell}\mathbf{W}_2 \\ \vdots \\ \boldsymbol{\Phi}_{N,\ell}\mathbf{W}_N \end{pmatrix}, \mathbf{h}_t = \begin{pmatrix} \mathbf{h}_{1,t} \\ \mathbf{h}_{2,t} \\ \vdots \\ \mathbf{h}_{N,t} \end{pmatrix} \text{and } \mathbf{u}_t = \begin{pmatrix} \mathbf{u}_{1,t} \\ \mathbf{u}_{2,t} \\ \vdots \\ \mathbf{u}_{N,t} \end{pmatrix} \sim \mathrm{IID}(0, \Sigma_{\mathbf{u}}).$$

In a final step, the dominant unit model $\mathbf{d_t}$ in the sense of Chudik and Pesaran (2013) needs to be integrated into the system, which is specified as

$$\mathbf{d}_t = \sum_{\ell=1}^{r_d} \boldsymbol{\Pi}_{t-\ell}\mathbf{d}_{t-\ell} + \boldsymbol{\lambda}_d t + \boldsymbol{\mu}_d + \mathbf{u}_{d,t}, \tag{4.6}$$

and where lagged feedback effects from the rest of the GVAR model are neglected for illustration purposes. Note first that the global variables enter each country model with their contemporaneous and lagged values, while potential feedback effects from the rest of the GVAR model are only allowed to enter with their lagged values.[23] Assuming that the $\mathbf{u}_{d,t}$ and $\mathbf{u}_t$ innovations are uncorrelated and defining the $(k + k_d) \times 1$ vector $\tilde{\mathbf{y}} = (\mathbf{y}'_t, \mathbf{d}'_t)'$ and $\mathbf{h}_{d,t} = \boldsymbol{\lambda}_d t + \boldsymbol{\mu}_d$, Equation

[23] See Chudik and Pesaran (2016) for the case of including feedback effects from the rest of the GVAR model.

(4.5) and Equation (4.6) can be summarized as

$$\tilde{\mathbf{G}}_0 \tilde{\mathbf{y}}_t = \sum_{\ell=1}^{p} \tilde{\mathbf{G}}_\ell \tilde{\mathbf{y}}_{t-\ell} + \tilde{\mathbf{h}}_t + \tilde{\mathbf{u}}_t, \tag{4.7}$$

where $p = \max(p_j, q_j, r, r_d)$ and for $\ell = 1, \ldots, p$

$$\tilde{\mathbf{G}}_0 = \begin{pmatrix} \mathbf{G}_0 & -\mathbf{C}_0 \\ \mathbf{0}_{k_d \times k} & \mathbf{I}_{k_d} \end{pmatrix}, \tilde{\mathbf{G}}_\ell = \begin{pmatrix} \mathbf{G}_\ell & \mathbf{C}_\ell \\ \mathbf{B}_\ell \mathbf{W}_j & \mathbf{A}_\ell \end{pmatrix}, \tilde{\mathbf{h}}_t = \begin{pmatrix} \mathbf{h}_t \\ \mathbf{h}_{d,t} \end{pmatrix} \text{ and } \tilde{\mathbf{u}}_t = \begin{pmatrix} \mathbf{u}_t \\ \mathbf{u}_{d,t} \end{pmatrix}.$$

Premultiplying Equation (4.7) by $\tilde{\mathbf{G}}_0^{-1}$ yields the autoregressive representation of the GVAR(p) model:

$$\tilde{\mathbf{y}}_t = \sum_{\ell=1}^{p} \mathbf{F}_\ell \tilde{\mathbf{y}}_{t-\ell} + \mathbf{f}_t + \boldsymbol{\upsilon}_t, \quad \boldsymbol{\upsilon}_t \sim \mathrm{IID}(0, \Sigma_{\boldsymbol{\upsilon}}) \tag{4.8}$$

with $\mathbf{F}_\ell = \tilde{\mathbf{G}}_0^{-1} \mathbf{G}_\ell$, $\ell = 1, \ldots, p$, $\mathbf{f}_t = \tilde{\mathbf{G}}_0^{-1} \tilde{\mathbf{h}}_t$ and $\boldsymbol{\upsilon}_t = \tilde{\mathbf{G}}_0^{-1} \tilde{\mathbf{u}}_t$ such that $\boldsymbol{\Sigma}_{\boldsymbol{\upsilon}} = \tilde{\mathbf{G}}_0^{-1} \boldsymbol{\Sigma}_{\tilde{\mathbf{u}}} \tilde{\mathbf{G}}_0^{-1\prime}$. Estimation of the GVAR model is performed by using the GVAR toolbox 2.0 by Smith and Galesi (2014).

4.4.2 Identification Through External Instrument

Stock and Watson (2012) and Mertens and Ravn (2013) introduced the identification method via external instruments, which can also be applied in the GVAR context. Note that the GVAR model given in Equation (4.7) features $K = k + k_d$ reduced form errors, of which $k = \sum_{j=1}^{N} k_j$ are unit-specific and k_d are associated with the common global variables, and which are collected in the vector $\tilde{\mathbf{u}}_t = (\mathbf{u}'_{1,t}, \mathbf{u}'_{2,t}, \ldots, \mathbf{u}'_{N,t}, \mathbf{u}'_{d,t})'$. Suppose that the reduced form errors are linearly related to the underlying structural shocks as follows:

$$\tilde{\mathbf{u}}_t = \boldsymbol{\Psi} \boldsymbol{\varepsilon}_t, \tag{4.9}$$

where $\boldsymbol{\varepsilon}_t$ is a $K \times 1$ vector of structural shocks, with $\mathbb{E}(\boldsymbol{\varepsilon}_t \boldsymbol{\varepsilon}'_t) = \mathbf{I}_K$ by construction. In general, identifying structural shocks within the GVAR model requires finding the $K \times K$ matrix of contemporaneous relations $\boldsymbol{\Psi}$ such that $\boldsymbol{\Sigma}_{\tilde{\mathbf{u}}} = \mathbb{E}(\tilde{\mathbf{u}}_t \tilde{\mathbf{u}}'_t) = \boldsymbol{\Psi}\boldsymbol{\Psi}'$. The external instrument approach to identification is build upon identifying the European bank balance sheet shock out of the K structural shocks contained in $\boldsymbol{\varepsilon}_t$. Denoting by the scalar ε_t^{bs} the balance sheet shock at time t and letting the $(K-1) \times 1$ vector $\boldsymbol{\varepsilon}_t^*$ include the remaining structural shocks, allows rewriting Equation (4.9) as:

$$\tilde{\mathbf{u}}_t = \boldsymbol{\psi}^{bs} \varepsilon_t^{bs} + \boldsymbol{\Psi}^* \boldsymbol{\varepsilon}_t^*, \tag{4.10}$$

where $\boldsymbol{\psi}^{bs}$ represents the impulse vector associated with the balance sheet shock and $\boldsymbol{\Psi}^*$ captures the impulse vectors of the remaining shocks. Identification of the balance sheet shock by means of the instrument constructed above requires that the instrument, denoted by $\mathbf{m}$, satisfies the following two conditions:

$$\begin{aligned} &1. \quad \mathbb{E}(\varepsilon_t^{bs} m_t) \neq 0 \qquad \text{(relevance)}, \\ &2. \quad \mathbb{E}(\boldsymbol{\varepsilon}_t^{*} m_t) = 0 \qquad \text{(exogeneity)}. \end{aligned} \tag{4.11}$$

The relevance condition states that the balance sheet shock needs to be related to the variations of the proxy, while the exogeneity condition says that the proxy has to be independent of any other shock in the system. Unfortunately, neither of the two conditions is directly testable as the true structural balance sheet shock is unobserved. However, regarding the relevance condition one can obtain a measure of the strength of the instrument based on its correlation with the estimated shock, as is done below. Meeting the exogeneity condition relies on two assumptions. First, note that the residuals of the panel regression given in Equation (4.1) which are used to construct the instrument are orthogonal to all regressors included in the regression. As the regression features global and country-specific macro-financial indicators as well as bank-specific factors that might be affected by other shocks, the instrument is assumed to be exogenous to traditional macroeconomic demand and supply, monetary and financial shocks. Second, as the panel regression does not control for local demand effects in all countries included in the GVAR model, it is further assumed that country-specific domestic factors do no contemporaneously affect the leverage of large European banks (cf. Cesa-Bianchi et al., 2018).

Given that the instrument satisfies these two conditions (4.11), it allows isolating the variations in the reduced form errors $\tilde{\mathbf{u}}_t$ that are driven by the balance sheet shock ε_t^{bs} from other structural shocks $\boldsymbol{\varepsilon}_t^{*}$ present in the system.[24] Stock and Watson (2012) and Mertens and Ravn (2013) demonstrate how the instrument can be utilized to consistently estimate the impulse vector $\boldsymbol{\psi}^{bs}$, which is required to identify the leverage shock ε_t^{bs}. Specifically, they propose to regress the reduced form residuals onto the instrument:

$$\hat{u}_{l,t} = \theta + \xi_k m_t + \tau_{l,t}, \qquad k = 1, \ldots, K, \tag{4.12}$$

where $\hat{u}_{l,t}$ is the estimated reduced form residual corresponding to equation l of model (4.7).[25] Given Equation (4.10) and the relevance and exogeneity condition (4.11), the regression allows to obtain the relative contemporaneous response of the variables in the GVAR model to a European bank balance sheet shock that shifts the instrument by a scaled amount.[26]

[24] It is further worth mentioning that the instrument is not required to be free from measurement errors, to be symmetric around zero, or to cover the entire sample period of the GVAR model (Piffer and Podstawski, forthcoming).

[25] Note that while the instrument is a generated regressor, the GVAR estimates are not distorted as the instrument is not included as an endogenous variable in the GVAR model. In particular, Pagan (1984) shows that OLS-based instrumental variable estimation with a generated regressor is asymptotically correct and yields a consistent estimator of the true standard errors.

[26] In detail, the relative contemporaneous response of the endogenous variables is given by $\psi_l^{bs}/\psi_\kappa^{bs}$ with κ denoting the equation in which the variable reflecting the balance sheet of European banks enters as a dependent variable. Given Equation (4.10) and the relevance and exogeneity condition (4.11), note that $\mathbb{E}(\mathbf{u}_t m_t) = \boldsymbol{\psi}^{bs}\mathbb{E}(\varepsilon_t^{bs} m_t)$, thus $\hat{\xi}_l \xrightarrow{p} \psi_l^{bs}\zeta$ with $\zeta = \mathbb{E}(\varepsilon_t^{bs} m_t)/\mathbb{E}(m_t)$ constant across l, and hence $\hat{\xi}_l/\hat{\xi}_\kappa \xrightarrow{p} \psi_l^{bs}/\psi_\kappa^{bs}$. That is, one can consistently estimate the contemporaneous impulse vector $\tilde{\boldsymbol{\psi}}^{bs}$, which differs from $\boldsymbol{\psi}^{bs}$ only up to a scalar ζ.

The estimate of the contemporaneous impulse vector, denoted by $\tilde{\boldsymbol{\psi}}^{bs}$, can then be employed to derive the vector of structural impulse response functions in the GVAR model by

$$\mathcal{IRF}(n) = \frac{\mathbf{R}_n \tilde{\mathbf{G}}_0^{-1} \tilde{\boldsymbol{\psi}}^{bs}}{\sqrt{\mathbf{e}_j' \boldsymbol{\Sigma}_{\tilde{\mathbf{u}}} \mathbf{e}_j}},$$

where $n = 0, 1, \ldots$ denotes the horizon, $\mathbf{e}_j$ is a $K \times 1$ selection vector that selects variable j and the $K \times K$ matrices $\mathbf{R}_n$ are obtained recursively as

$$\mathbf{R}_n = \sum_{\ell=1}^{p} \mathbf{F}_\ell \mathbf{R}_{n-\ell} \text{ with } \mathbf{R}_0 = \mathbf{I}_K \text{ and } \mathbf{R}_\ell = \mathbf{0} \text{ for } \ell < 0.$$

The statistical significance of the effects of the balance sheet shock is evaluated by computing 68% and 95% confidence bands of the impulse responses, respectively. As a bootstrap method a residual-based wild design bootstrap is applied.[27] For illustration purposes, I aggregate the single country impulse responses to aggregated regional impulse responses by weighting the single country ones according to their average GDP weight within the region in the period 1999 to 2016. See Table 4.7 in Appendix 4.A for an overview of the regions and the corresponding country weights in constructing them.

4.4.3 Data and Model Specification

The GVAR model contains in total 30 observation units, composed of 29 countries plus the eurozone which enters as one single unit (see Table 4.7 in Appendix 4.A). The data are at quarterly frequency and encompass the time period 1999Q1 to 2016Q4, yielding in sum 72 observations per each unit. In order to investigate the effects of the European bank balance sheet shock on economic activity and financial conditions abroad, I compute the impulse responses of real GDP growth, the short-term real interest rate, gross capital inflows, and real credit growth in the sample countries. However, due to the rather short sample period it is not advisable to estimate a single large model that includes all variables of interest at once. Consequently, I consider two different small-scale VARX specifications, one focusing on the effects of the balance sheet shock on capital flows and the other one on credit growth:

$$\begin{aligned}
\mathbf{y}_{j,t} &= (\text{real GDP growth, real interest rate, gross capital inflows})' \quad \forall j, \\
\mathbf{y}^*_{j,t} &= (\text{real GDP growth, real interest rate})' \quad \forall j \neq \text{U.S.}, \qquad \text{(Model (I))} \\
\mathbf{y}^*_{US,t} &= (\text{real GDP growth})',
\end{aligned}$$

[27] Applying the residual-based moving block algorithm of Jentsch and Lunsford (2016) results in slightly broader confidence bands, turning the impulse response of the real interest rate for some regions and of the VIX insignificant.

$$\begin{aligned}\mathbf{y}_{j,t} &= (\text{real GDP growth, real interest rate, real credit growth})' \quad \forall\, j,\\ \mathbf{y}^*_{j,t} &= (\text{real GDP growth, real interest rate})' \quad \forall\, j \neq \text{U.S.}, \qquad\qquad \text{(Model (II))}\\ \mathbf{y}^*_{US,t} &= (\text{real GDP growth})',\end{aligned}$$

where as above $\mathbf{y}_{j,t}$ represents the vector of domestic endogenous variables and $\mathbf{y}^*_{j,t}$ the vector of country-specific foreign variables. In Model (I) gross capital inflows refer to the sum of the net incurrence of liabilities of portfolio investment and other investment (including cross-border loans) obtained from the IMF BOPS database. First, note that the measure does not include foreign direct investment as they are distinct since the primary aim is to gain control of a business and also exhibit a rather low correlation with other types of capital flows (Rey, 2013). Second, I choose gross inflows as net inflows hide the true extent of capital flows, inter alia, because of the well-documented "round-tripping" of capital flows by European banks (Avdjiev et al., 2016). The different treatment of the U.S. unit regarding inclusion of foreign weakly exogenous variables is due to the predominant role of U.S. monetary policy (Rey, 2013, Miranda-Agrippino and Rey, 2018). Given that real GDP and real credit enter the VARX models in first (log-)differences, I abstain from estimating long-term cointegration relationships among the countries. Again, this is primarily attributed to the rather short sample period that on top includes the recent global financial crisis with heterogenous effects among countries.

An important question concerns the choice of the aggregate bank balance sheet measure as well as its inclusion in the GVAR model. Given the aim of reflecting the leverage cycle of European banks, I take the log-difference of the ratio of total assets of monetary financial institutions in the European Union to European nominal GDP. This choice is motivated by several reasons. First, this measure captures best how the size of the European banking sector changes in relation to the European real economy. Second, considering total assets implies that only changes in the leverage of European banks are modeled that are driven by a change in assets and not by the liability side through raising equity. Third, taking the ratio with respect to GDP contributes in ensuring that supply side factors are underlying the identified shock as arguably demand factors would likely change total bank assets and GDP simultaneously. Turning to the inclusion of this variable in the GVAR model, note that including it as an endogenous variable in a specific European VARX model appears unnatural as the measure is an European aggregate. Instead, I model it as a global variable in the dominant unit that enters weakly exogenous to all European VARX models, but not to any other, non-European, units. Furthermore, to control for global risk aversion and uncertainty I add the VIX to the global unit and as a weakly exogenous variable to all country-specific VARX models.[28] Taken together, the dominant unit is specified in both VARX model specifications as follows:

$$\mathbf{d}_t = (\text{Change of total assets of European banks over GDP, VIX})'.$$

[28] Including the VIX is motivated by findings that it is a driver of capital flows, global liquidity, and banks' leverage (Forbes and Warnock, 2012, Rey, 2013, Nier et al., 2014, Bruno and Shin, 2015b, Cerutti et al., 2017).

Regarding the link matrices employed in constructing the foreign variables in the VARX models, the natural choice in the analysis of European bank balance sheet shocks would be bilateral banking flows. Unfortunately, country and time coverage of the international banking statistics of the Bank for International Settlements is smaller than the sample considered in the analysis. Given these limitations, link matrices are as usual based on bilateral trade flows, constructed as the sum of exports and imports between two units, averaged over the whole sample period.

In Section 4.5.5 I perform several robustness checks to these baseline specifications, including inter alia a specification in which the aggregate balance sheet measure enters as an endogenous variable in the eurozone VARX as the largest European economy in the sample and a specification in which I add a commodity price index to the dominant unit.

4.5 Results

This section presents the main results of analyzing the effects of European bank balance sheet shocks in the GVAR model. After briefly discussing the strength of the instrument used to identify the balance sheet shock, effects of the shock in the model containing capital inflows and subsequently in the model featuring credit are shown and compared among regions. The focus is on aggregate grouped impulse responses, with three different classifications of single economies into groups being considered: a simple geographical one as baseline, one based on financial depth, and one using the number of European banks present in a country. Finally, I briefly summarize all performed robustness checks, concerning both the instrument and the GVAR specification.

4.5.1 Strength of the Instrument

As common, I test the strength of the instrument by assessing the correlation between the instrument and the estimated reduced form shocks (cf. Gertler and Karadi, 2015, Piffer and Podstawski, forthcoming). Technically, I obtain the reliability statistics by running regression (4.12) of the estimated reduced form shocks on a constant and the instrument for all equations in the GVAR model (4.7). Table 4.2 reports the first-stage F-statistic and the corresponding reliability measure (Mertens and Ravn, 2013) of the instrument with respect to the European banks assets-to-GDP variable for both model specifications, as well as the correlation between the instrument and the identified shock. Given an F-statistic of close to 30 and hence clearly above 10, the null hypothesis that the coefficient corresponding to the equation of the aggregated bank assets-to-GDP residual is zero is rejected, suggesting that the instrument is not weak (Stock et al., 2002). The reliability statistic is around 0.50 which translates into a correlation between the instrument and the identified shock of around 0.70.[29] Reassuringly, for all other variables in Model (I) and all but one in Model (II) the first-stage F-statistic is below 10, the exception being the residual corresponding to Brazilian real credit growth with a F-statistic

[29] Note that the correlation between the instrument and the identified shock is equal to the square root of the reliability statistic.

Table 4.2: Statistics on the Strength of the Instrument

	F-statistic	Reliability	Correlation with Shock
Model (I)	29.30	0.50	0.71
Model (II)	29.30	0.47	0.69

Note: The table reports the first-stage F-statistic and the corresponding reliability measure of the instrument with respect to the European banks assets-to-GDP variable for both model specifications as well as the correlation between the instrument and the shock. These statistics are obtained from running regression (4.12) of the estimated reduced form shocks on a constant and the instrument.

slightly above ten (13.51). While it is advisable to keep this in mind when interpreting in particular the quantitative impact of the identified shock on Brazilian (and in further consequence South American) credit growth, it seems implausible that an idiosyncratic Brazilian credit shock drives European total bank assets. Hence, taken together these statistics provide evidence that the constructed instrument is indeed capturing European bank balance sheet shocks.

Figure 4.9 in Appendix 4.B plots the estimated structural shocks for both model specifications. Naturally, there are some differences between them as also the reduced-form residuals in the GVAR individual VARX models differ. The differences are, however, minor, which is reflected in a high correlation between the two identified shocks of 0.90. In sum, the estimated balance sheet shocks seem to be consistent with the narrative one can tell about European bank behavior in the last two decades. The upcoming sections analyze the effects of a typical negative European bank balance shock, that is of deleveraging, in the GVAR model.[30]

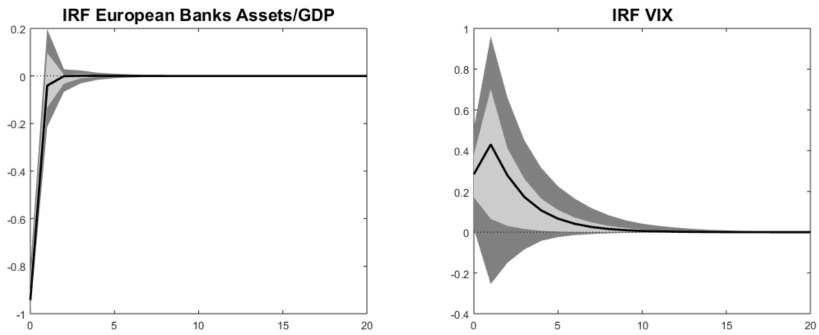
4.5.2 Results Model (I)

I now turn to the estimated impulse responses to the European bank balance sheet shock in Model (I) featuring capital inflows. In the following, I first present results for the dominant unit and for six different aggregated geographical regions, which are composed of individual economies according to GDP PPP weights as stated in Table 4.7 in Appendix 4.A. To save space, I do not show impulse responses of all individual economies, but the euro zone, Switzerland, UK, and the U.S. as important financial centers given in Figure 4.13 in Appendix 4.B.

To start with, note that the estimated structural shock corresponds to a decrease in the growth rate of the European banks assets-to-GDP ratio of approximately 0.90 percentage points on impact and that the effect is very short-lived, as depicted in Figure 4.2. The estimate of the impulse response is highly significant and precisely estimated as indicted by the narrow 68% (light gray) and wider 95% (dark gray) bootstrapped confidence intervals, respectively. Furthermore, deleveraging of European banks leads to a significant increase of the implied volatility index VIX on impact, with the effect fading out only after almost two years.

[30] Note first that applying an external instrument identifies a shock up to a sign convention and second that given the GVAR model the effects of positive and negative shocks are exactly symmetric.

Figure 4.2: Impulse Responses of European Banks Assets/GDP and VIX - Model (I)

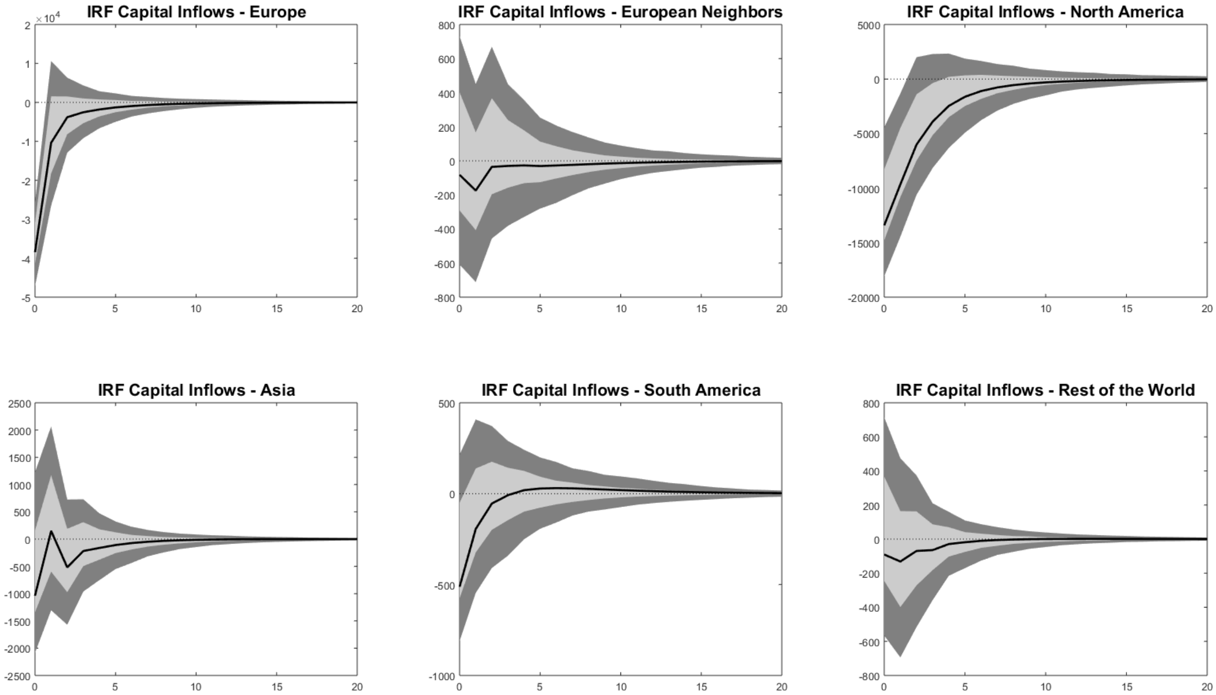


Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the dominant unit of the Model (I) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. The vertical axis is in percentage points in case of European Banks Assets/GDP and in absolute values in case of the VIX, respectively, and horizontal axes are in quarters.

Figure 4.3 shows the impulse responses of gross capital inflows to different geographical regions. Starting with Europe, the estimated impulse response of capital inflows is strongly negative and highly significant. This holds true when looking at single European economies like the eurozone, Switzerland, or the U.K. (Figure 4.13 in Appendix 4.B). The result might be partly due to reduced capital flows within Europe, potentially pointing towards European banks cutting back their intra-European cross-border claims. Interestingly, there is no significant effect on capital inflows to a European bank balance sheet shock in the region encompassing neighboring countries (ISR, RUS, TUR) to Europe. In contrast, there is a strong and significantly negative response of capital inflows to North America, which is driven by a pronounced reduction in capital inflows to the U.S. (Figure 4.13 in Appendix 4.B). Capital inflows to both Asia and South America react negative as well, however, the measured impact is much smaller in magnitude than in case of North America and only marginally significant with respect to the broad 68% confidence band. In case of the region labeled “Rest of the World” (AUS, NZL, ZAF) capital inflows are not significantly affected in the aggregate. Figure 4.15 in Appendix 4.B compares the country-individual magnitude of the impact and shows that capital inflows decrease especially strong in the eurozone, Switzerland, the UK, and the U.S. as important financial centers. Compared to other countries in the sample, also the Nordic countries Denmark, Norway and Sweden as well as Canada, Japan and Hong Kong (positive impact) exhibit a quantitatively strong impact effect of capital inflows (note the different scale of the two bar plots in the figure).

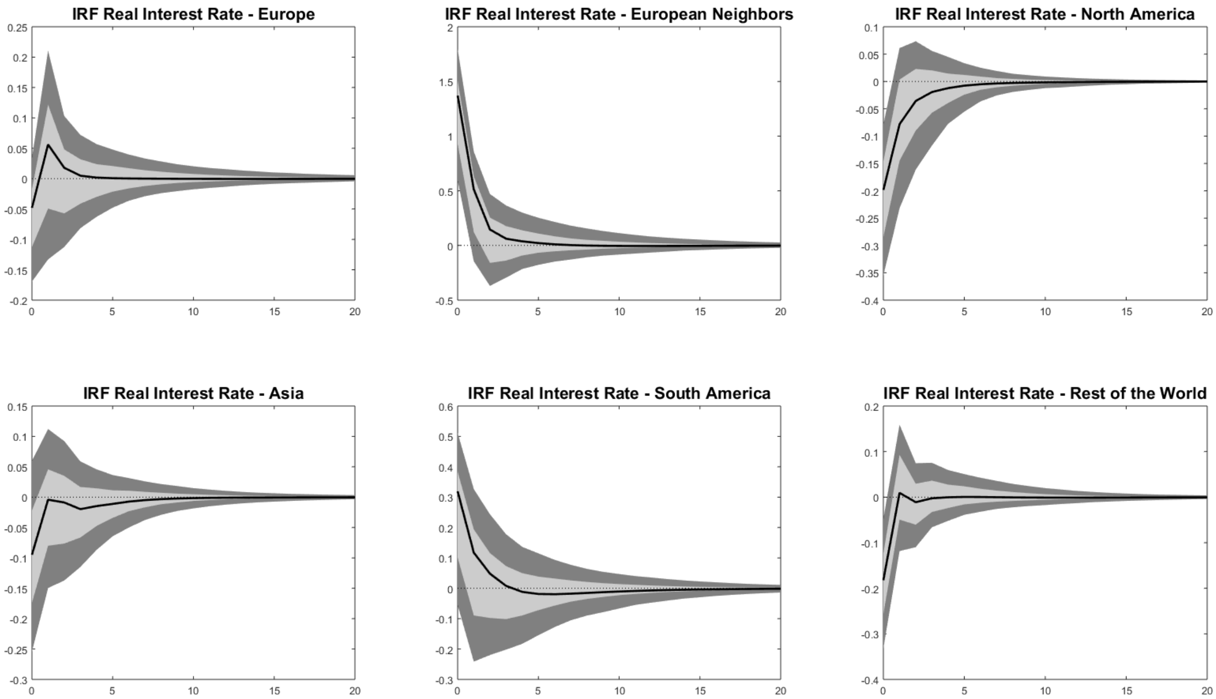
Next, the response of the real short-term interest rate across regions provided in Figure 4.4 indicates that the aggregate real interest rate in Europe reacts just slightly and is only marginally significantly negative on impact. Looking at impulse responses of individual units reveals that there is quite some heterogeneity among the European economies in the sample. In the eurozone the impulse response is positive for the first quarters after the shock, but the effect is not significant (Figure 4.13 in Appendix 4.B). Since real interest rates are considered, it cannot be

Figure 4.3: Regional Impulse Responses of Gross Capital Inflows - Model (I)



Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for aggregate regional gross capital inflows of the Model (I) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in absolute values and horizontal axes are in quarters.

Figure 4.4: Regional Impulse Responses of Real Short-Term Interest Rate - Model (I)

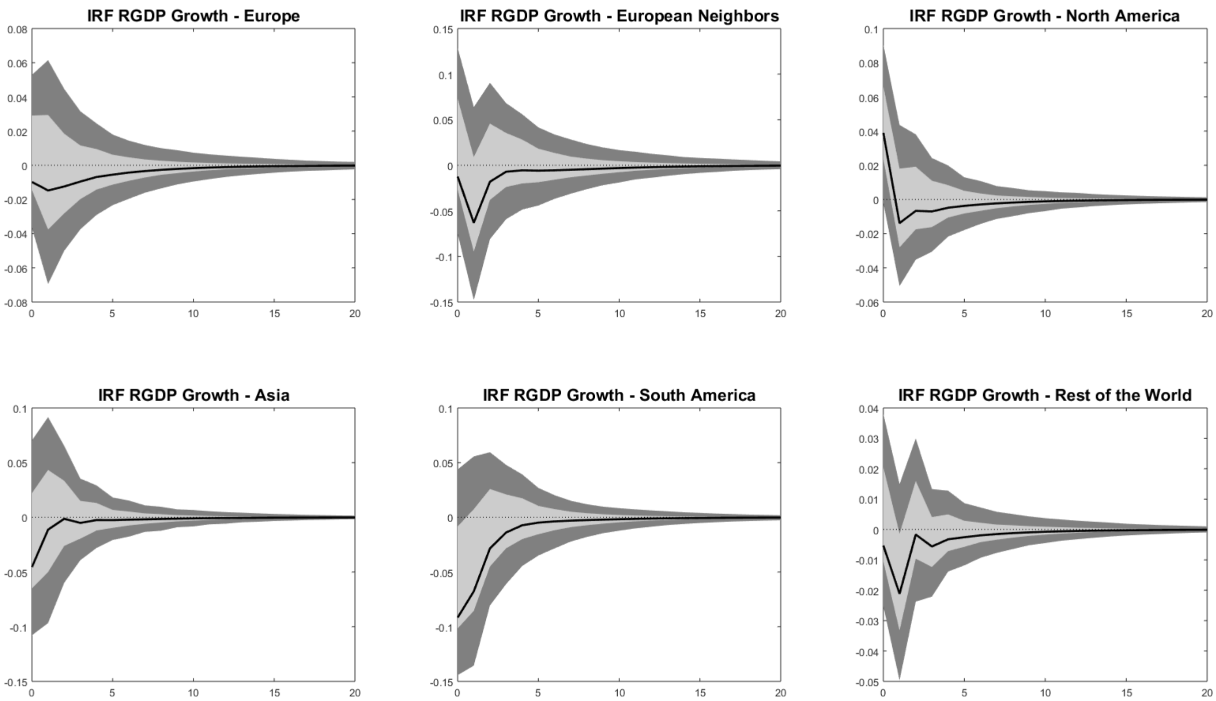


Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the aggregate regional real short-term interest rate of the Model (I) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters.

assessed how the nominal rate reacts as deleveraging by European banks potentially could also affect the inflation rate. In contrast, the real interest rate in Switzerland and the UK significantly decreases in response to the balance sheet shock (Figure 4.13 in Appendix 4.B), as well as in Denmark and Sweden (not shown). Regarding the other regions, there also is a significant decline in the real interest rate in North America, Asia (only with regards to the 68% confidence interval), and the in the "Rest of the World" region, whereas in European neighboring countries (driven solely by Turkey) and in South America (in all countries but Brazil) the real interest rate increases.

Regarding real GDP growth, Figure 4.5 indicates that balance sheet shocks of European banks do not have a significant impact on aggregate real output growth in almost all regions. Even though the impulse response is negative for all but one region, the confidence bands are fairly wide. The exception is North America, which exhibits a positive and marginally significant effect on regional real GDP growth, despite a strong decrease in capital inflows. Turning to European individual economies, there is a non-significant effect in the eurozone and Switzerland, but a marginally significantly negative impact in the UK (with regards to the 68% confidence interval).

Figure 4.5: Regional Impulse Responses of Real GDP Growth - Model (I)



Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for aggregate regional real GDP growth of the Model (I) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters.

Taken together, this result suggests that deleveraging of European banks significantly reduces capital inflows to several countries, but does not adversely affect real economic activity in the majority of them. To shed more light on this finding, in the next section investigates impulse responses of Model (II) that includes real credit growth instead of gross capital inflows.

4.5.3 Results Model (II)

Model (II) equals Model (I) except of exchanging gross capital inflows with real credit growth as endogenous variable in the country-specific VARX models. As the impulse responses of the dominant unit (European banks assets-to-GDP and VIX), the real short-term interest rate and real GDP growth are very similar to the ones in Model (I), they are not discussed again and the corresponding graphs are provided in Appendix 4.B, Figures 4.10 to 4.12. The only differences worth mentioning are a less negative impact of real GDP growth in South America and the "Rest of the World" region as well as a negative response of the real interest rate in South America in the first quarters after the impact of the balance sheet shock.[31]

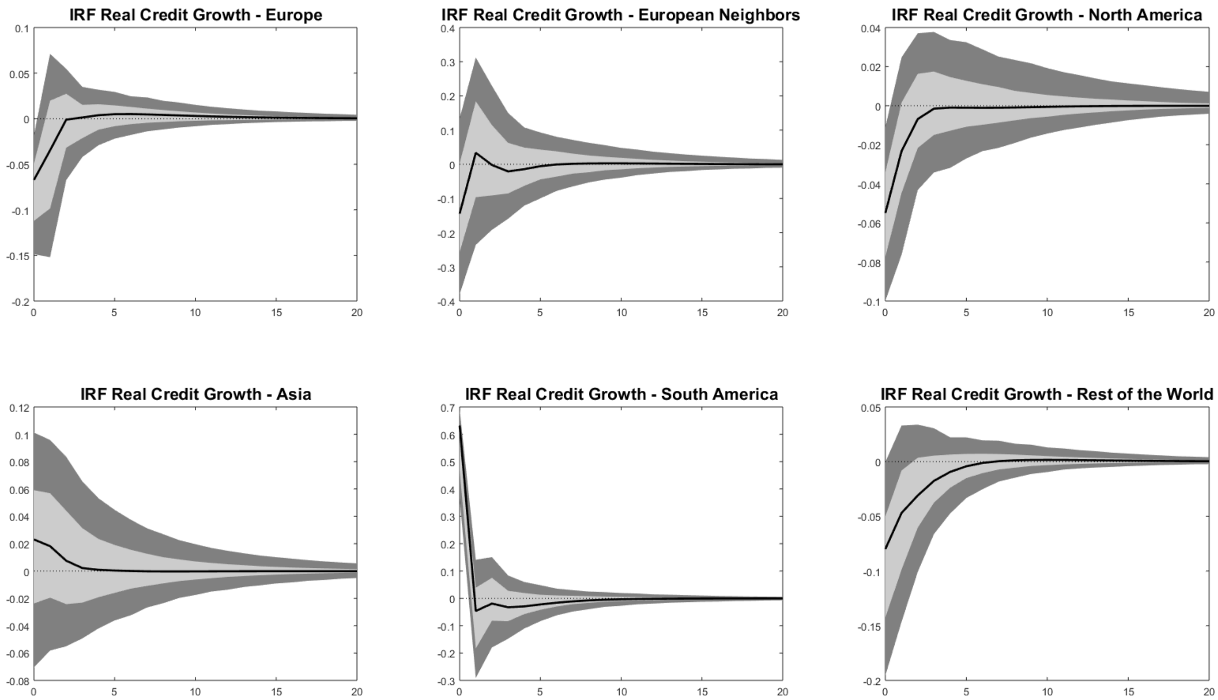
Figure 4.6 shows the aggregated regional impulse responses of real credit growth to the European bank balance sheet shock and Figure 4.16 in Appendix 4.B the unit-specific effects on impact. The response is significantly negative and pronounced in Europe and North America[32], the two regions for which also the decrease in capital inflows is found to be the strongest, as well as in the "Rest of the World" region. The impact is also quantitatively large in the region of European neighboring countries, however, the effect is short-lived and only marginally significant with respect to the 68% confidence band. In Asia real credit growth is not significantly affected at the aggregate regional level, but there is considerable country heterogeneity with some affected significantly negative (for example Japan) and some significantly positive (for example India). In contrast, in South America real credit growth increases markedly after the balance sheet shock. While this holds true for all four South American countries in the sample (ARG, BRA, CHL, COL), the result should nevertheless be treated with caution as the instrument is also slightly related to the residuals in the Brazilian credit equation (see above) and hence might also pick up Brazilian credit shocks to some extent.

In sum, the findings in Model (I) and Model (II) provide empirical evidence that European bank balance sheet shocks affect gross capital inflows and real credit growth in countries across different geographical regions, but have only minor effects on real output growth. As expected, bank balance sheet shocks have weaker effects on credit and especially on real output than typical

[31] The difference in the responses of the real interest rate and real GDP growth in South America is mainly driven by Brazil. Given that in case of Model (II) the F-statistic of regressing the residual of the Brazilian credit equation on the instrument is slightly above ten (see above), this result should be treated with caution.

[32] The significantly negative effect on capital inflows and real credit growth in combination with a marginally significantly positive effect on real GDP growth in North America, driven by the U.S., seems implausible. A vague interpretation would be that a bank balance sheet shock forces European banks to withdraw productive and unproductive credit from the U.S., with excessive credit in the U.S. housing market being an example for the latter. In turn, U.S. banks might attempt to partly fill the emerging gap and to increase their market share, but provide only credit for productive business sectors. The overall effect would thus be negative for capital inflows and credit growth, while output could potentially increase.

Figure 4.6: Regional Impulse Responses of Real Credit Growth - Model (II)



Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for aggregate regional real credit growth of the Model (II) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters.

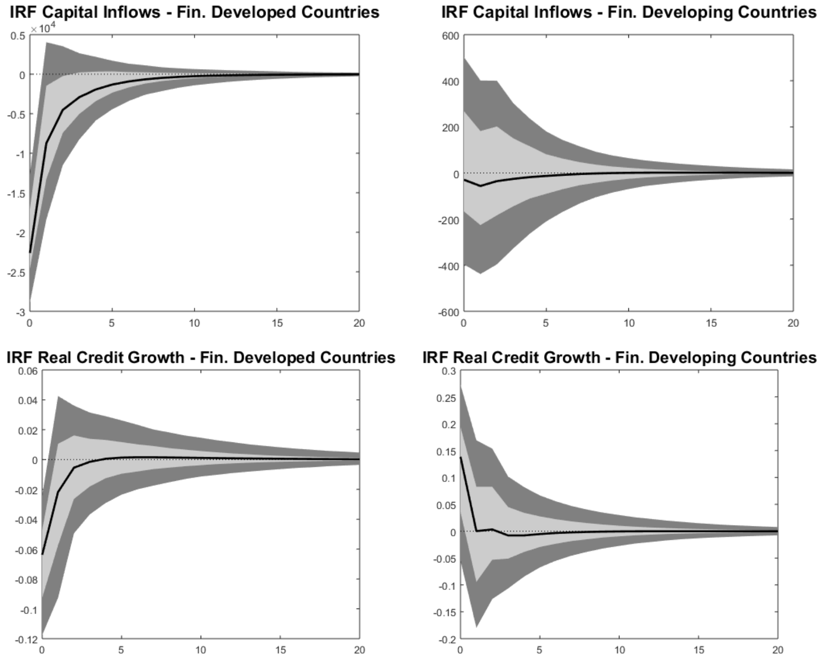
sign-restricted credit supply shocks (Eickmeier and Ng, 2011, Fadejeva et al., 2015). A bank can change its leverage ratio in various ways with a different impact on its lending behavior and hence on credit supply to the non-financial private sector. For example, an ordered deleveraging process might involve withdrawing from speculative and unproductive investments with little effect on real economic activity, while traditional loan supply to firms and households might be less affected. Moreover, letting the impulse response of total credit and real output unrestricted allows for the possibility that the private non-financial sector is able to draw on other sources of financing than bank loans, keeping the overall effect on economic activity relatively small.

4.5.4 Different Aggregations

Given a non-negligible degree of heterogeneity across countries belonging to the same geographical region, this section presents aggregate impulse responses for different classifications of countries into groups.[33] First, I use the total credit-to-GDP ratio averaged over the sample period as a measure for financial depth to separate countries into financially developed (above median value) and financially developing (below median value) economies. Figure 4.7 shows the aggre-

[33] Note that the impulse responses of the two variables in the dominant unit, that is, European banks assets over GDP and the VIX, are not affected by different aggregation methods of countries to regions.

Figure 4.7: Grouped Impulse Responses of Gross Capital Inflows and Real Credit Growth - Financial Depth/Development



Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for aggregate grouped gross capital inflows (Model (I), upper panel) and aggregate grouped real credit growth (Model (II), lower panel). The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in absolute values in case of gross capital inflows and in percentage points in case of real credit growth, respectively, and horizontal axes are in quarters.

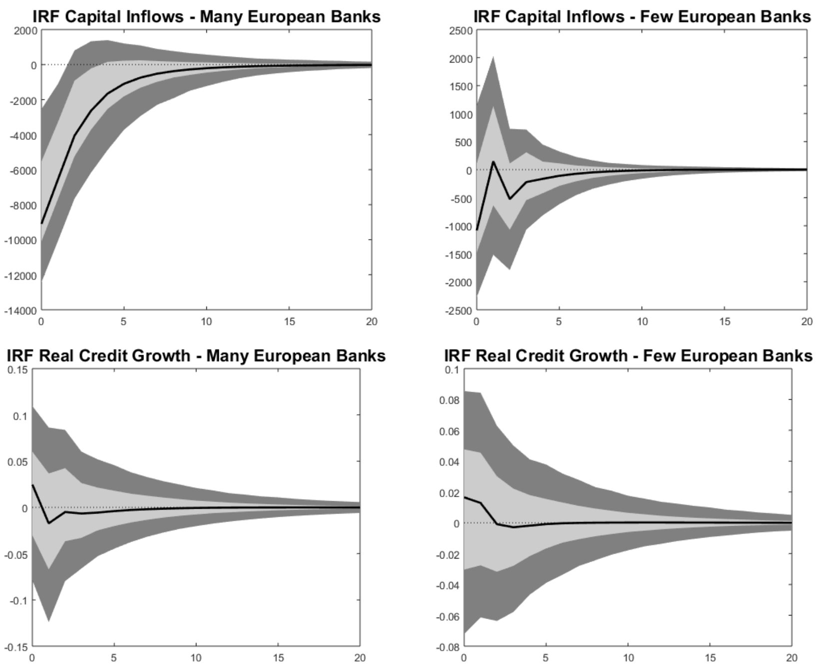
gate impulse response of capital inflows (Model (I), upper panel) and real credit growth (Model (II), lower panel). The differences between the two country groups are marked: in financially developed countries gross capital inflows and real credit growth decrease significantly in response to a European bank balance sheet shock, whereas in the other group capital inflows are hardly affected and real credit growth actually increases significantly with respect to the 68% confidence band. Furthermore, the real interest rate significantly decreases in financially developed countries, while it increases in the group of financially developing countries (Figure 4.17 in Appendix 4.B). Only with regards to real GDP growth there is no difference between the two country groups as both impulse responses are insignificant (Figure 4.17 in Appendix 4.B). This result also holds for other classifications of countries into groups as using the total credit-to-GDP ratio yields country groups similar to those obtained from employing other classification variables. Specifically, this applies to classifying countries according to their degree of financial openness as measured by the Chinn-Ito-Index (Chinn and Ito, 2006), according to a simple differentiation of countries into advanced and emerging economies, as well as according to the quality of their institutions along four dimensions of the World Governance Indicators.[34] This finding squares

[34] These results are not reported, but are available upon request.

with narratives about the behavior of European banks in the last decades. Prior to the crisis European banks were heavily engaged in the lending boom in southern European countries as well as in the U.S., or to put differently in advanced economies. In the wake of the financial crisis and during the sovereign debt crisis in the eurozone, European banks withdrew money from both regions. In contrast, emerging markets were less affected from the global financial crisis and have been considered as growth markets (Feyen and del Mazo, 2013), in particular during times of low interest rates in advanced economies.

Figure 4.8 displays the aggregate impulse responses of gross capital inflows (Model (I), upper panel) and real credit growth (Model (II), lower panel) of country groups created according to the number of European banks present in the country. Ideally, one would like to classify countries according to the share of assets of European banks in total bank assets in that country, but unfortunately such data is not publicly available to the best of my knowledge. As an alternative, I use the database on foreign banks of Claessens and van Horen (2014) and group countries based whether the number of European banks in a specific country is above or below the cross-country median of the sum over the sample period. Importantly, I exclude European countries in creating the two groups. In this case there are less pronounced differences between the two

Figure 4.8: Grouped Impulse Responses of Gross Capital Inflows and Real Credit Growth - Number of European Banks



Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for aggregate grouped gross capital inflows (Model (I), upper panel) and aggregate grouped real credit growth (Model (II), lower panel). The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in absolute values in case of gross capital inflows and in percentage points in case of real credit growth, respectively, and horizontal axes are in quarters.

groups. In both groups of countries capital inflows are adversely affected, although the impact is quantitatively far weaker and only marginally significant in the group featuring a lower number of EU banks. With respect to real credit growth, there are no differences as impulse responses for both groups are insignificant. The same is true for the real short-term interest rate and real GDP growth, albeit the estimated impulse responses differ a bit between the two groups on impact (Figure 4.18 in Appendix 4.B). In particular, the real interest rate decreases significantly with respect to the 68% confidence band in the group of countries with fewer European banks.

Overall, these findings suggest that European bank balance sheet shocks impact on capital inflows to and real credit growth in advanced economies with developed financial markets. Emerging market economies with less developed financial markets tend to be less affected. The sheer number of European banks present in a country seems to be of subordinate importance.

4.5.5 Robustness Checks

This section briefly outlines several robustness checks that have been performed to test the sensitivity of results to different specifications of the GVAR model as well as different instruments. To save space, impulse responses of these checks are not provided, but are available upon request.

The first set of robustness checks concerns the instrument employed to identify the balance sheet shock of European banks. First, I use the baseline instrument without winsorizing it and second apply two different methods in aggregating the bank-individual residuals: instead of taking the median, I once take the average and next I weight the residuals by the size of the bank according to its total assets (see Figure 4.19 in Appendix 4.B). Third, I keep the baseline panel and aggregation specification but use the residuals obtained from employing the two different estimators, namely the cross-sectional time-series FGLS estimator and the FE estimator featuring AR(1) residuals (see Figure 4.20 in Appendix 4.B). Next, I create on the one hand an instrument derived from a panel specification that only controls for macro-financial conditions but not for bank-individual characteristics (see column three in Table 4.1), thereby increasing the number of total observations, and on the other hand an instrument derived from a panel specification that additionally includes a survey-based measure on credit demand in the eurozone from the Bank Lending Survey of the European Central Bank[35] (see Figure 4.21 in Appendix 4.B). I further indirectly control for the global financial crisis by setting the instrument to zero for the observations between 2008Q1 and 2009Q4, implying that this period does not provide any information for the identification of the balance sheet shocks of European banks. Finally, I also set the baseline instrument to zero until 2001Q4 to ensure that results are not driven by the first

[35] Ideally, one would include country-specific measures on credit demand. Unfortunately, such data is for quite a few European countries either not publicly available (for example, Finland or Sweden) or starts quite late (for example, 2007Q2 for the UK). This is the main reason why the baseline specification does not include this variable and why the eurozone-wide weighted diffusion-index (weighted sum of demand for credit from enterprises, for consumer credit, and for credit for house purchases), which is available since 2003Q1, is applied here.

observations of the instrument that are based on a rather small number of banks for which data is available and which at the same time exhibit some large values.

The second set of robustness checks examines the sensitivity of the results to changes in the specification of the GVAR model. First, I keep the baseline GVAR specification, but repeat all analyses with taking a simple average across countries when computing the regional/grouped impulse responses instead of applying country-specific GDP PPP weights. In this way the aggregate impulse responses are not primarily driven by the largest economy of a region/group. Second, I estimate models in which I substitute gross capital inflows based on the sum of portfolio flows and other capital flows with gross capital inflows based solely on the latter, that is, excluding portfolio flows (Model (I)), as well as bank credit with credit from all lenders (Model (II)). Third, I test the sensitivity of the results with respect to the European banks assets-to-GDP variable. The construction of this variable is subject to two potential caveats. First, for some countries data are available only at a later stage of the sample, meaning that incorporating them might bias the variable at these specific quarters. Second, original data for Norway and Switzerland is denoted in domestic currency and converted to Euro by applying the quarterly end-of-period spot exchange rate, creating the possibility of valuation effects. As both these shortcomings only affect few countries, the overall effect on the final aggregate variable is negligible. Nonetheless, I check the results by employing two alternative measures for the aggregate banks assets-to-GDP variable: one which is just based on countries for which data are available over the whole sample period 1999Q1-2016Q4 and another one in which Norway and Switzerland are excluded (these series have a correlation with the original variable of 0.9850 and 0.9964, respectively). Moreover, instead of incorporating this variable in the dominant unit of the GVAR model that enters the VARX models of European economies as weakly exogenous, I model it as an endogenous variable in the eurozone VARX model as the largest European economy and as weakly exogenous to all other European economies. Fourth, I include additional variables in the dominant unit, namely an IMF commodity price index since for many countries in the sample commodity prices - especially oil prices - play an important role in determining a country's trade balance and economic activity, and the Global Economic Activity Index of Kilian (2009). Fifth, I enlarge the country-specific VARX models with the real effective exchange rate obtained from the database of Darvas (2012) as a fourth endogenous variable. Sixth, instead of employing trade weights for the link matrices between the sample units, I use bilateral banking flow data from the BIS consolidated banking statistics. However, as data on banking flows is available only for a limited number of countries in the sample this comes at the cost of obtaining a weighting matrix with a lot of empty entries, that is, without an interdependence between two economies. Last, I change some comparatively minor settings of the baseline GVAR model, namely allowing for feedback effects between the dominant unit variables and the VARX variables, applying the sample covariance matrix instead of a block-diagonal covariance matrix in the baseline specification, and changing the treatment of the deterministic components of the GVAR model (allowing for unrestricted intercepts and restricted trends instead of allowing only for restricted intercepts in the baseline specification).

In sum, the vast majority of these alterations to the baseline specification regarding both, the instrument and the GVAR model, yield results in terms of impulse responses that are qualitatively and in many cases also quantitatively similar to the baseline results. Only four deviations are worth mentioning. First, when aggregating country-specific impulse response to grouped ones by simply taking the average, the impulse response of the short-term real interest rate turns significantly positive for the group featuring many European banks. Second, in those robustness checks in which the instrument is zero at the beginning of the sample, which includes the panel specification that controls for credit demand, the VIX exhibits a significantly negative impulse response. Third, if the residuals from the panel regression applying the cross-sectional time series FGLS estimator are used to construct the instrument, then the impulse response of the VIX is negative as well while the impulse response of real GDP growth turns significantly positive for some regions, including Europe and North America. Fourth, in case the instrument is constructed by taking either the average or the weighted sum of the bank-individual residuals instead of taking the median, the impulse response of the VIX is again significantly negative and in case of the regions European Neighbors, South America, and "Rest of the World" capital inflows become positive. In addition, for some regions the impulse response of real GDP growth and the short-term real interest rate changes. However, these deviations are mainly driven by outliers in the alternative instruments in the quarters 2005Q4, 2006Q4, 2008Q1 and 2008Q4 (see Figure 4.19 in Appendix 4.B), which all can be traced back to outliers of one or two single banks in that specific quarter and bias the instrument.[36] Overall, the results with respect to capital inflows and credit growth, in particular for advanced economies, are very robust across all these alternative specifications.

4.6 Conclusion

In the last two decades, European banks have been key actors in the global financial system and important providers of credit in advanced and emerging economies alike. Their lending behavior acts as a potentially significant channel of the global transmission of financial conditions. Until the global financial crisis, European banks were substantially increasing their balance sheet, in particular by cross-border lending. Since then, they had to adjust their business models and meet new regulatory requirements, inducing them to deleverage on a large scale. This process was amplified by the sovereign debt crisis in the euro area that hit their balance sheet only a few years after the shockwaves of the global financial crisis.

Against this background, I propose a simple approach to identify supply-induced structural shocks to the balance sheet of large European banks based on the methodology of Stock and Watson (2012) and Mertens and Ravn (2013) and analyze the international spillovers in a GVAR

[36] In detail, in 2005Q4 these are UBS and Commerzbank, in 2006Q4 Deutsche Bank and Credit Suisse, in 2008Q1 Deutsche Bank and in 2008Q4 Deutsche Bank and UBS.

model. The results suggest that European bank balance sheet shocks significantly affect gross capital inflows and real credit growth in countries across different geographical regions, but have only minor effects on real output growth in the majority of countries and geographical regions. Looking at aggregated country groups, advanced economies that are also financially developed and open are generally more affected than emerging market economies with less developed and less open financial markets. In contrast, the sheer number of European banks present in a country seems to be of subordinate importance. These results are robust to a range of sensitivity analyses regarding both, the construction of the instrument and the specification of the GVAR model. Overall, the results support the introduction of regulatory constraints on specific measures of leverage of (European) banks which capture overall leverage, currency-specific leverage and cross-border leverage in addition to the commonly implemented constraint on risk-adjusted leverage (Ivashina et al., 2015, Avdjiev et al., 2016).

Nonetheless, there are some caveats one has to be aware of when interpreting the results. First and foremost, the panel of European banks applied to construct the external instrument is fairly unbalanced. Especially during the first quarters the sample is rather small and misses some important banks. Second, while the panel regression controls for a range of macro-financial and bank-specific factors, the validity of the constructed instrument relies on the assumption that non-European country-specific factors do no contemporaneously affect the leverage of European banks. Given these limitations, a reassessment of the analysis with better data seems warranted. Altogether, there is still a lot to be learnt from the lending and investment decisions of global European banks and their implications for global financial and macroeconomic conditions.

4.A Data Appendix

Table 4.3: Large European Banks Included in the Panel Regression

Bank	Country	Bloomberg Symbol	First Observation	No. of Obs.
HSBC Holdings	GBR	HSBA LN	2007Q2/2011Q1	32/22
BNP Paribas	FRA	BNP FP	2007Q4/2012Q3	27/15
Credit Agricole Group	FRA	ACA FP	2007Q1/2008Q3	39/30
Deutsche Bank	DEU	DBK GR	2001Q3/2003Q1	62/55
Barclays PLC	GBR	BARC LN	2001Q2/2012Q3	41/13
Societe Generale	FRA	GLE FP	2007Q2/2010Q1	34/19
Banco Santander	ESP	SAN SM	1999Q1/2000Q2	71/65
Lloyds Banking Group PLC	GBR	LLOY LN	2007Q2/2011Q1	33/14
Royal Bank of Scotland	GBR	RBS LN	2007Q4/2009Q1	34/27
UBS Group AG	CHE	UBSG VX	1999Q2/2002Q3	61/47
UniCredit S.p.A.	ITA	UCG IM	2000Q1/2001Q2	67/38
ING Group	NLD	INGA NA	1999Q1/2001Q1	72/37
Credit Suisse Group	CHE	CSGN VX	2001Q1/2002Q2	64/59
BBVA (Banco Bilbao Vizcaya Argentaria SA)	ESP	BBVA SM	1999Q1/2000Q2	72/66
Intesa Sanpaolo	ITA	ISP IM	2000Q2/2001Q3	66/40
Nordea Bank	SWE	NDA SS	1999Q1/1999Q3	72/65
Commerzbank AG	DEU	CBK GR	2000Q1/2001Q2	58/52
Danske Bank	DNK	DANSKE DC	2000Q1/2001Q2	68/51
ABN AMRO Group	NLD	ABN NA	2012Q1/2016Q2	20/3
CaixaBank	ESP	CABK SM	2010Q1/2011Q2	28/23
DNB Group	NOR	DNB NO	1999Q1/1999Q3	72/62
KBC Group NV	BEL	KBC BB	2003Q1/2004Q2	53/44
Svenska Handelsbanken	SWE	SHBA SS	1999Q1/1999Q4	72/69
Skandinaviska Enskilda Banken	SWE	SEBA SS	1999Q1/1999Q3	72/64
Swedbank	SWE	SWEDA SS	1999Q1/2000Q2	72/67
Banco Sabadell	ESP	SAB SM	2001Q1/2002Q2	64/59
Erste Group Bank AG	AUT	EBS AV	1999Q1/2000Q2	70/64
Bankia	ESP	BKIA SM	2011Q1/2014Q1	19/12
Banco Bpm SpA	ITA	BAMI IM	2007Q2/2010Q1	38/13
Banco Popular Espanol	ESP	POP SM	1999Q1/2000Q2	72/67
OP Financial Group	FIN	POH1S FH	2004Q1/2006Q1	51/15
UBI Banca	ITA	UBI IM	2004Q1/2005Q3	52/46
Caixa Geral de Depositos	PRT	CXGD PL	2008Q1/-	36/0

Note: The table lists all the banks included in the panel regression applied to construct the external instrument for identifying European bank balance sheet shocks. Extreme outliers of leverage ratios have been excluded from the panel, namely UBS Group AG 2007Q4-2008Q1, Commerzbank AG 2008Q4-2011Q1, KBC Group NV 2009Q1-Q2, and Erste Group Bank AG 2002Q1-Q2. Regarding the last two columns, the first entry refers to the first observation and the total number of observations of the leverage ratio for a bank, while the second entry reports the quarter of the first observation and the total number of observations for which all bank-specific factors are available, that is, the number of observations in the full specification panel model.
A robustness check that controls only for macro-financial conditions but not for bank-specific factors and hence involves the larger number of observations yields an instrument that is very similar to the baseline model (see Figure 4.21 in Appendix 4.B, correlation of 0.89 with the baseline instrument) and identifies a bank balance sheet shock with qualitatively similar effects in terms of impulse responses. Regarding capital inflows and real credit growth, merely the impact on capital inflows turns significantly for Asia (with respect to the 95% confidence interval) and the region European Neighbors (with respect to the 68% confidence interval); some other few differences are only of quantitative nature. However, this alternative instrument is less informative as indicated by a lower first-stage F-statistic of 13.56, compared to 29.30 of the baseline instrument. The full set of results for this robustness check is available upon request.

Table 4.4: Variables in the Panel Regression

Variable	**Definition and Source**
Leverage	Calculated as total assets over total common equity. Bloomberg, symbols: BS_TOT_ASSET, TOT_COMMON_EQY.
Real GDP Growth	Gross domestic product at market prices, 2010 chained linked volumes, Million Euro, seasonally and calendar adjusted, first log-differences. Eurostat, series code: namq_10_gdp.
Unemployment Rate	Harmonised unemployment rate, all persons, seasonally adjusted. OECD Statistics. Switzerland: unemployment rate as defined by the International Labour Organization. Swiss Federal Statistical Office.
Credit/GDP	Credit to the private non-financial sector from banks, market value, percentage of GDP, adjusted for breaks. BIS.
EONIA Rate	Weighted rate for the overnight maturity, percent, average of observations through period. ECB Statistical Data Warehouse, series code: EON.D.EONIA_TO.RATE.
Federal Funds Rate	Effective federal funds rate, Percent, average of period. Federal Reserve Bank of St. Louis, Federal Reserve Economic Data (FRED), series code: FEDFUNDS.
VSTOXX	Euro Stoxx 50® volatility, average of period. Available at: https://www.stoxx.com/document/Indices/Current/HistoricalData/h_v2tx.txt (08/24/2018).
EBP	Excess Bond Premium, average of period. Gilchrist and Zakrajšek (2012b), available at: http://people.bu.edu/sgilchri/Data/data.htm - 'Credit spread and excess bond premium data (updated through August 2016)' (08/24/2018).
FX USD/EUR	ECB reference exchange rate, US dollar/Euro, 2:15 pm (C.E.T.), average of period. ECB Statistical Data Warehouse, series code: EXR.D.USD.EUR.SP00.A.
U.S. Broker-Dealers Leverage	Ratio of total financial assets to the difference between total financial assets and total liabilities of security brokers and dealers. Board of Governors of the Federal Reserve System, Financial Accounts of the United States, Z.1 Statistical Release for September 21, 2017, series codes: FL664090005.Q and FL664190005.Q, respectively.
ln(Assets)	Sum of cash & bank balances, Fed funds sold & resale agreements, investments for trade and sale, net loans, investments held to maturity, net fixed assets, other assets, customers' acceptances and liabilities. Natural logarithm. Bloomberg, symbol: BS_TOT_ASSET.
ROA	Return on assets, calculated as trailing 12-month net income divided by average total assets, multiplied by 100. Bloomberg, symbol: RETURN_ON_ASSET.
Tobin's q	Ratio of the market value of a firm to the replacement cost of the firm's assets. Bloomberg, symbol: TOBIN_Q_RATIO.
Stock Return	Last price for the security. First log-differences. Bloomberg, symbol: PX_LAST.
Deposits/Assets	Total deposits as a percentage of total assets. Bloomberg, symbol: DEPOSITS_TO_ASSETS.
Loans/Deposits	Total loans as a percentage of total deposits. Bloomberg, symbol: TOT_LOAN_TO_TOT_DPST.
Credit Demand	Weighted sum of euro area weighted diffusion indices of demand for credit for enterprises, consumer credit and credit for house purchases. Overall, backward looking three months, single weighted diffusion indices are based on the share of each country in the total loan outstanding amounts of the area aggregate, also weighted with the share of each bank in the total loan outstanding amount of the banks in the Bank Lending Survey (BLS) sample. ECB Statistical Data Warehouse, BLS, series codes: BLS.Q.U2.ALL.O.E.Z.B3.ZZ.D.BWDINX (enterprises), BLS.Q.U2.ALL.Z.H.C.B3.ZZ.D.BWDINX (consumer credit), BLS.Q.U2.ALL.Z.H.H.B3.ZZ.D.BWDINX (house purchases).

Note: The table reports all variables included in the full specification of the panel regression applied to derive the external instrument.

Table 4.5: Summary Statistics of Variables in the Panel Regression

Variable	Observations	Mean	Standard Deviation	Minimum	Maximum
Leverage	1764	23.14	9.17	9.72	71.73
Real GDP Growth	2376	0.39	0.77	-7.09	3.45
Unemployment Rate	2376	8.65	4.72	2.40	26.23
Credit/GDP	2376	103.24	30.19	42.70	199.50
EONIA Rate	2376	1.87	1.61	-0.35	4.84
Federal Funds Rate	2376	1.98	2.13	0.07	6.52
VSTOXX	2376	25.14	8.67	13.06	58.34
EBP	2343	0.08	0.69	-0.82	2.64
FX USD/EUR	2376	1.21	0.17	0.87	1.56
U.S. Broker-Dealers Leverage	2376	22.74	5.71	14.29	36.48
ln(Assets)	1793	12.80	1.09	9.49	14.76
ROA	1623	0.39	0.51	-1.91	2.64
Tobin's q	1690	1.01	0.04	0.93	1.25
Stock Return	1801	-1.17	19.99	-128.74	97.09
Deposits/Assets	1711	37.38	11.33	7.40	74.49
Loans/Deposits	1590	145.81	60.02	40.25	475.32

Note: The table reports summary statistics of the variables included in the full specification of the panel regression applied to derive the external instrument, after cleaning the original data.

Table 4.6: Correlation among Variables in the Panel Regression

	Leverage	Real GDP Growth	Unemployment Rate	Credit/ GDP	EONIA Rate	Federal Funds Rate	VSTOXX	EBP
Leverage	1.0000							
Real GDP Growth	-0.0238	1.0000						
Unemployment Rate	-0.3524	-0.1189	1.0000					
Credit/GDP	0.0259	-0.1084	0.2924	1.0000				
EONIA Rate	0.2379	0.0532	-0.2885	-0.1713	1.0000			
Federal Funds Rate	0.1542	0.2935	-0.2572	-0.1881	0.8234	1.0000		
VSTOXX	0.0940	-0.4282	-0.0448	0.0224	0.1454	-0.2081	1.0000	
EBP	0.0826	-0.4568	-0.0847	-0.0148	0.3323	0.0242	0.7367	1.0000
FX USD/EUR	0.0377	-0.1848	0.0657	0.2965	-0.2169	-0.2658	-0.1839	-0.2204
U.S. Broker-Dealers Lev.	0.2800	0.0260	-0.2680	-0.0431	0.8460	0.7180	-0.0151	0.0988
ln(Assets)	0.3567	-0.0849	-0.0465	0.1496	-0.3770	-0.3366	-0.0558	-0.0929
ROA	-0.2086	0.2442	-0.0764	-0.0165	0.4532	0.4955	-0.1041	0.0073
Tobin's q	0.0189	0.3522	-0.1574	-0.0227	0.5538	0.6049	-0.1601	-0.0291
Stock Return	0.0045	0.1833	-0.0223	-0.0015	-0.0873	0.0468	-0.3610	-0.3202
Deposits/Assets	-0.4992	0.0065	0.4039	-0.1209	-0.1807	-0.1278	-0.0434	-0.0275
Loans/Deposits	-0.2465	-0.0197	-0.0482	0.0909	0.2275	0.1710	0.0693	0.1017

Note: The table reports the correlation among the variables included in the full specification of the panel regression applied to derive the external instrument, after cleaning the original data.

Table 4.6 ctd.: Correlation among Variables in the Panel Regression

	FX USD/ EUR	U.S. Broker-Dealers Lev.	ln(Assets)	ROA	Tobin's q	Stock Return	Deposits/ Assets	Loans/ Deposits
FX USD/EUR	1.0000							
U.S. Broker-Dealers Lev.	0.1788	1.0000						
ln(Assets)	0.2134	-0.2716	1.0000					
ROA	-0.1493	0.4162	-0.3827	1.0000				
Tobin's q	-0.2884	0.4503	-0.3677	0.6783	1.0000			
Stock Return	-0.0176	-0.0345	-0.0320	0.0720	0.1995	1.0000		
Deposits/Assets	-0.1534	-0.2515	-0.1952	0.0971	0.0455	-0.0036	1.0000	
Loans/Deposits	0.0422	0.2196	-0.5519	0.2140	0.1191	0.0076	-0.3904	1.0000

Note: The table reports the correlation among the variables included in the full specification of the panel regression applied to derive the external instrument, after cleaning the original data.

Table 4.7: GVAR Units and Their Classification into Regions Based on GDP PPP Weights

Unit	Geographical Region						Financial Depth		# EU Banks	
	Asia	EU	EUN	NA	RoW	SA	High	Low	Many	Few
Argentina						0.19		0.04	0.02	
Australia					0.57		0.02		0.03	
Brazil						0.62		0.13	0.08	
Canada				0.08			0.03		0.05	
Chile						0.07		0.02	0.01	
Colombia						0.12		0.03		0.03
Czech Republic		0.02						0.02		
Denmark		0.01					0.01			
Eurozone		0.71					0.29			
Hong Kong SAR	0.02						0.01			0.02
Hungary		0.01						0.01		
India	0.32							0.25		0.32
Indonesia	0.11							0.08	0.05	
Israel			0.06					0.01		0.02
Japan	0.34						0.11			0.34
Korea	0.11						0.04			0.11
Malaysia	0.03						0.01			0.03
Mexico				0.09				0.09	0.06	
New Zealand					0.08		0.00			0.01
Norway		0.02					0.01			
Poland		0.04						0.04		
Russia			0.66					0.14	0.09	
Singapore	0.02						0.01			0.02
South Africa					0.35			0.03		0.04
Sweden		0.02					0.01			
Switzerland		0.02					0.01			
Thailand	0.05							0.04		0.05
Turkey			0.29					0.06	0.04	
United Kingdom		0.14					0.06			
United States				0.84			0.38		0.56	

Note: The table reports the classification of countries into geographical regions and groups, respectively, together with their respective weight in the region/group. "EU" refers to Europe, "EUN" to European Neighbors, "NA" to North America, "RoW" to Rest of World, and "SA" to South America.

Table 4.8: Definition of Variables

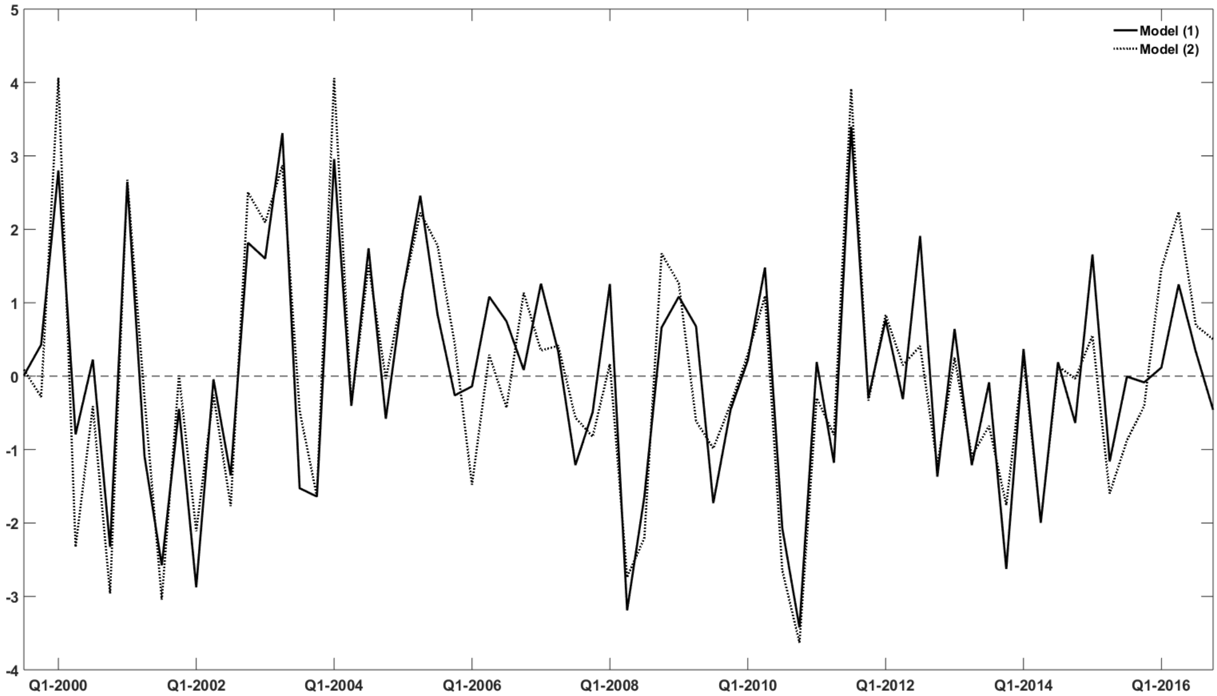
Variable	Definition and Source
Real GDP Growth	Gross domestic product, expenditure approach, national currency, volume estimates, OECD reference year, annual levels, seasonally adjusted, first log-differences. OECD Quarterly National Accounts, Series code: VOBARSA. For Colombia only available from 2000Q2 onwards. Hong Kong SAR: gross domestic product, real, reference chained, seasonally adjusted, domestic currency, first log-differences. Malaysia: gross domestic product, real, spliced historical series, domestic currency, seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment, first log-differences. Singapore: gross domestic product, real, domestic currency, seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment. Thailand: gross domestic product, seasonally adjusted, domestic currency, first log-differences. Deflated by gross domestic product, deflator, seasonally adjusted. All IMF International Financial Statistics (IFS), National Accounts.
Real Interest Rate	Immediate interest rates, call money, interbank rate, percent per annum. OECD Monthly Monetary and Financial Statistics (MEI). Deflated by consumer prices, all items, index, 2010=100, seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment, applying the formula $i_t - 4 * \Delta CPI_t * 100$. OECD Consumer Prices. Argentina: money market interest rate, percent per annum. Hong Kong SAR: Treasury Bill rate, percent per annum. Malaysia, Singapore, and Thailand: monetary policy-related interest rate, percent per annum. All IMF IFS, Interest Rates. Argentina: deflated by gross domestic product deflator, percentage change from previous period. IMF IFS, National Accounts. Hong Kong SAR, Singapore, and Thailand: deflated by using consumer price index, all items, index, 2010=100. IMF IFS, Prices, Production and Labor selected indicators. For Thailand only available from 2000Q3 onwards (set to zero before), for Malaysia the variable is excluded as it is only available from 2004Q2 onwards.
Gross Capital Inflows	Sum of net incurrence of liabilities of portfolio investment and other investment (robustness check: only other investment). IMF Balance of Payments Statistics, Financial Account. For New Zealand and Poland only available from 2000Q1 (set to zero before), for Malaysia the variable is excluded as it is only available from 2001Q1 to 2009Q4.
Real Credit Growth	Credit to private non-financial sector from all sectors (robustness check: from banks) at market value, domestic currency, adjusted for breaks, first log-differences. BIS, Long series on total credit to the non-financial sectors. For the eurozone only available from 1999Q2 onwards and for Indonesia from 2000Q1 onwards (set to zero before). Deflated by consumer prices, all items, index, 2010=100, seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment. OECD Consumer Prices. Argentina: deflated by gross domestic product deflator, percentage change from previous period. IMF IFS, National Accounts. Hong Kong SAR, Malaysia, Singapore, and Thailand: deflated by using consumer price index, all items, index, 2010=100. IMF IFS, Prices, Production and Labor selected indicators.
Bank Assets/GDP	Ratio of total assets of European financial institutions to European GDP. Quarterly, end of period, first log-differences. Assets: sum of total assets/liabilities reported by Monetary and Financial Institutions excluding European System of Central Banks (ESCB) of 30 European countries, quarterly, end of period, all currencies combined. ECB Statistical Data Warehouse, Balance Sheet Items (BSI), Series code: BSI.M.XX.N.A.T00.A.1.Z5.0000.Z01.E with 'XX' being substituted with country codes (AT/BE/BG/CY/CZ/DE/DK/EE/ES/FI/FR/GB/GR/HR/HU/IE/IT/LT/LU/LV/MT/NL/PL/PT/RO/SE/SI/SK).

Bank Assets/GDP ctd.	Norway: Statistics Norway, Statbank, banking and financial markets, 07880: Financial corporations, balance sheet, banks, total assets, monthly, NOK millions. Converted to Euro by using ECB reference exchange rate, Norwegian krone/Euro, 2:15 pm (C.E.T.), end of period. Series code: EXR.M.NOK.EUR.SP00.E. Switzerland: Swiss National Bank (SNB) data portal, banks, balance sheet items, total assets, domestic banks, all currencies, monthly, CHF millions. Converted to Euro by using ECB reference exchange rate, Swiss franc/Euro, 2:15 pm (C.E.T.), end of period. Series code: EXR.M.CHF.EUR.SP00.E. GDP: sum of gross domestic product at market prices of 30 European countries, current prices, Million Euro, seasonally and calendar adjusted (SVK: only seasonally adjusted). Eurostat, Series code: namq_10_gdp. Sample (first observation): AUT (full), BEL (full), BGR (2004Q1), CHE (1999Q1), CYP (2005Q4), CZE (2002Q1), DEU (full), DNK (2000Q3), ESP (full), EST (2008Q1), FIN (full), FRA (full), GBR (1999Q1), GRC (full), HRV (2010Q4), HUN (2003Q1), IRL (full), ITA (full), LTU (2004Q2), LUX (full), LVA (2010Q3), MLT (2005Q1), NLD (full), NOR (2009Q2), POL (2004Q1), PRT (full), ROU (2004Q4), SVK (2006Q1), SVN (2004Q1), SWE (2001Q4).
VIX	CBOE Volatility Index. Quarterly, end of period. Federal Reserve Bank of St. Louis, Federal Reserve Economic Data (FRED), Series code: VIXCLS.
Real Effective Exchange Rate	Real effective exchange rate (CPI-based) considering 138 trading partners. Quarterly, end of period, first log-differences. Darvas (2012), available at: `http://bruegel.org/publications/datasets/real-effective-exchange-rates-for-178-countries-a-new-database/` (09/19/2018)
Commodity Price Index	All Commodity Price Index (2005=100). Seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment, quarterly, end of period, first log-differences. IMF Primary Commodity Prices, Series code: PALLFNF.
Global Economic Activity	Global real economic activity in industrial commodity markets. Monthly percent deviations from trend, 01/1968-09/2017, seasonally adjusted using X-13ARIMA-SEATS Seasonal Adjustment, quarterly, end of period, first absolute differences. Kilian (2009), available at: `http://www-personal.umich.edu/~lkilian/reaupdate.txt` (09/19/2018)
Link Matrices	Trade weights (baseline): Annual sum of total exports and total imports between two countries. UN Comtrade Database. Banking flow weights (robustness check): Annual average of total claims of domestic banks of the reporting country to all sectors of the counterparty country, all instruments, all maturities, all currencies, ultimate risk basis. BIS Consolidated Banking Statistics.

Note: The table reports the variables included in the two GVAR model specifications as well as in the robustness checks thereof.

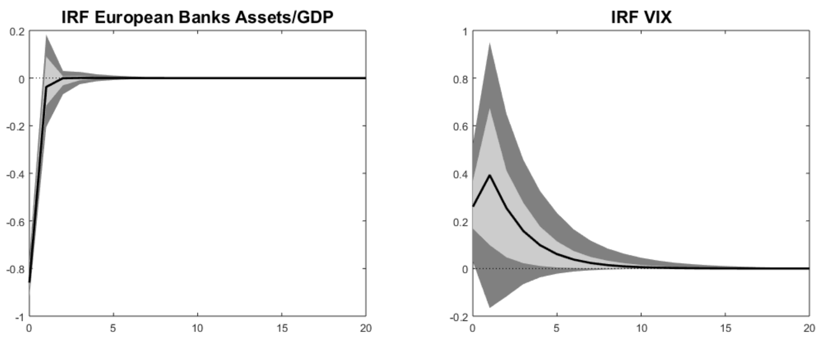
4.B Further Figures

Figure 4.9: Estimated European Bank Balance Sheet Shocks



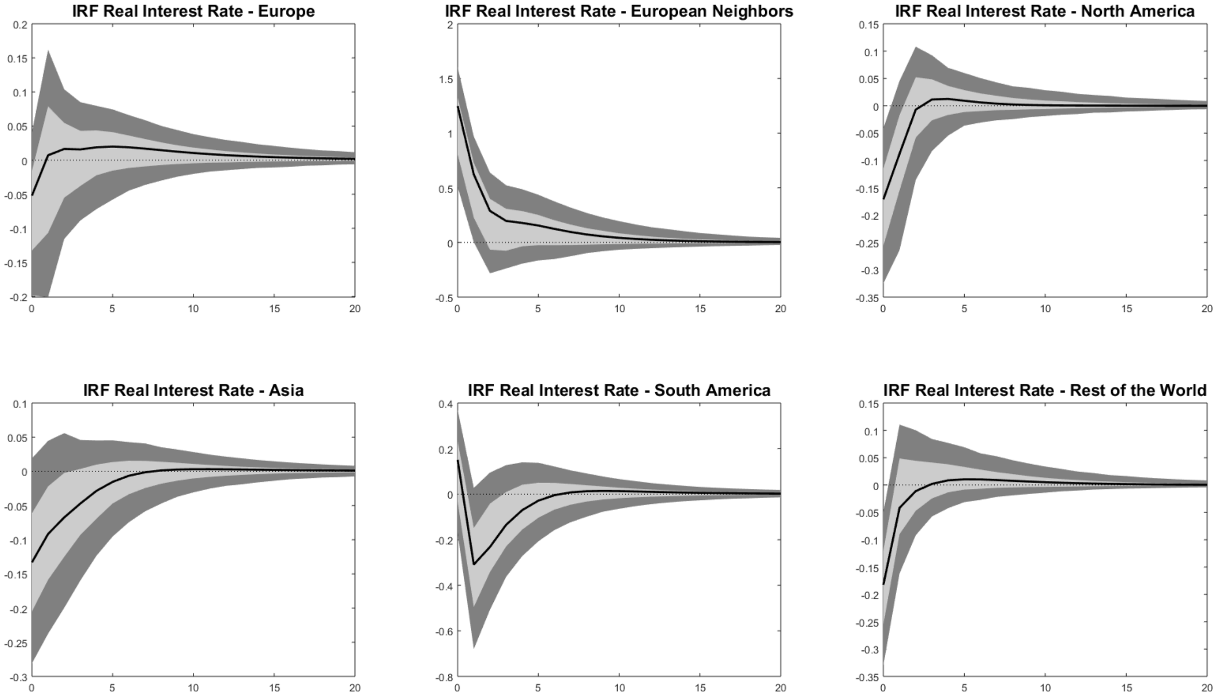
Note: The figure shows the estimated structural European bank balance sheet shocks for both GVAR model specifications. The vertical axis is in standard deviations.

Figure 4.10: Impulse Responses of European Banks Assets/GDP and VIX - Model (II)



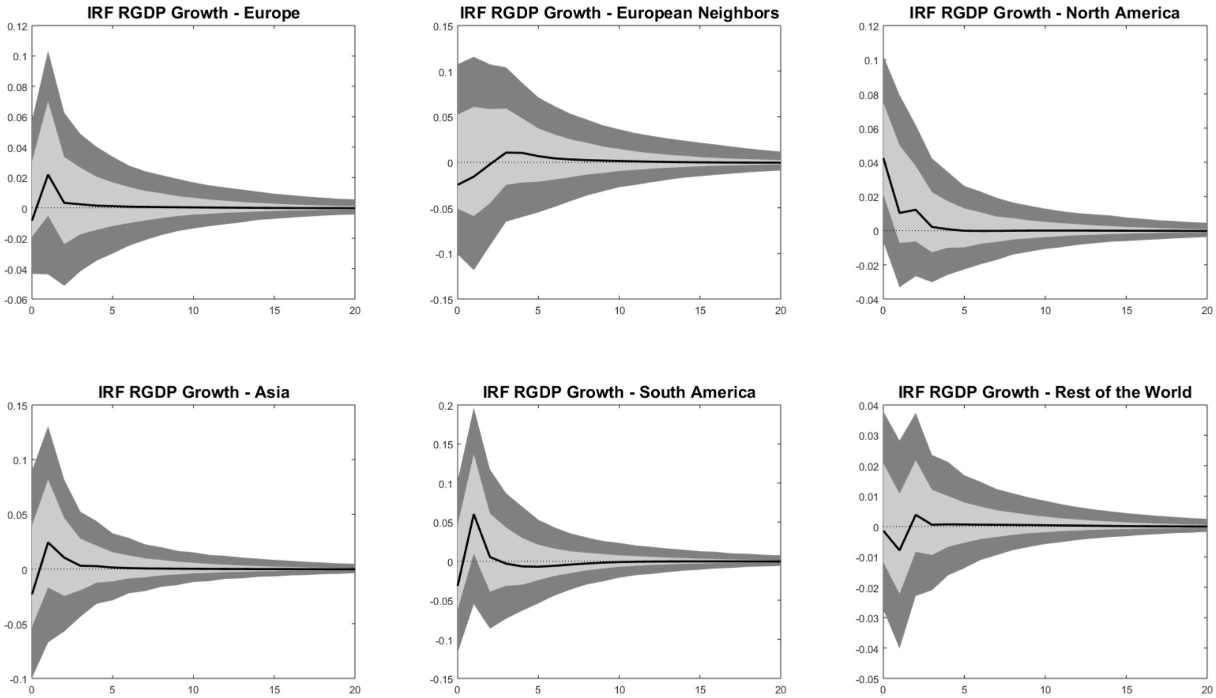
Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the dominant unit of the Model (II) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. The vertical axis is in percentage points in case of European Banks Assets/GDP and in absolute values in case of the VIX, respectively, and horizontal axes are in quarters.

Figure 4.11: Regional Impulse Responses of Real Short-Term Interest Rate - Model (II)



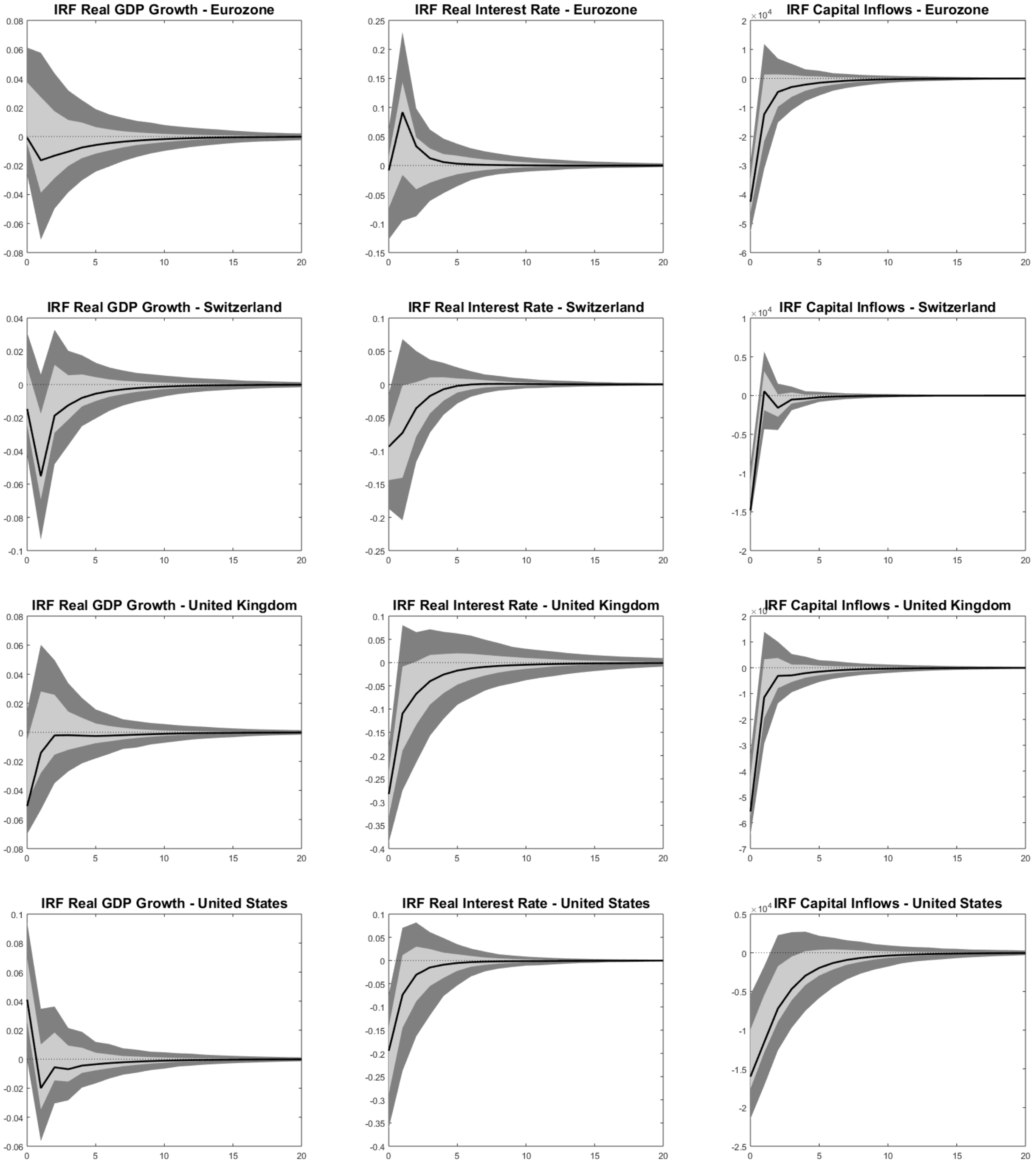
Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the aggregate regional real short-term interest rate of the Model (II) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters.

Figure 4.12: Regional Impulse Responses of Real GDP Growth - Model (II)



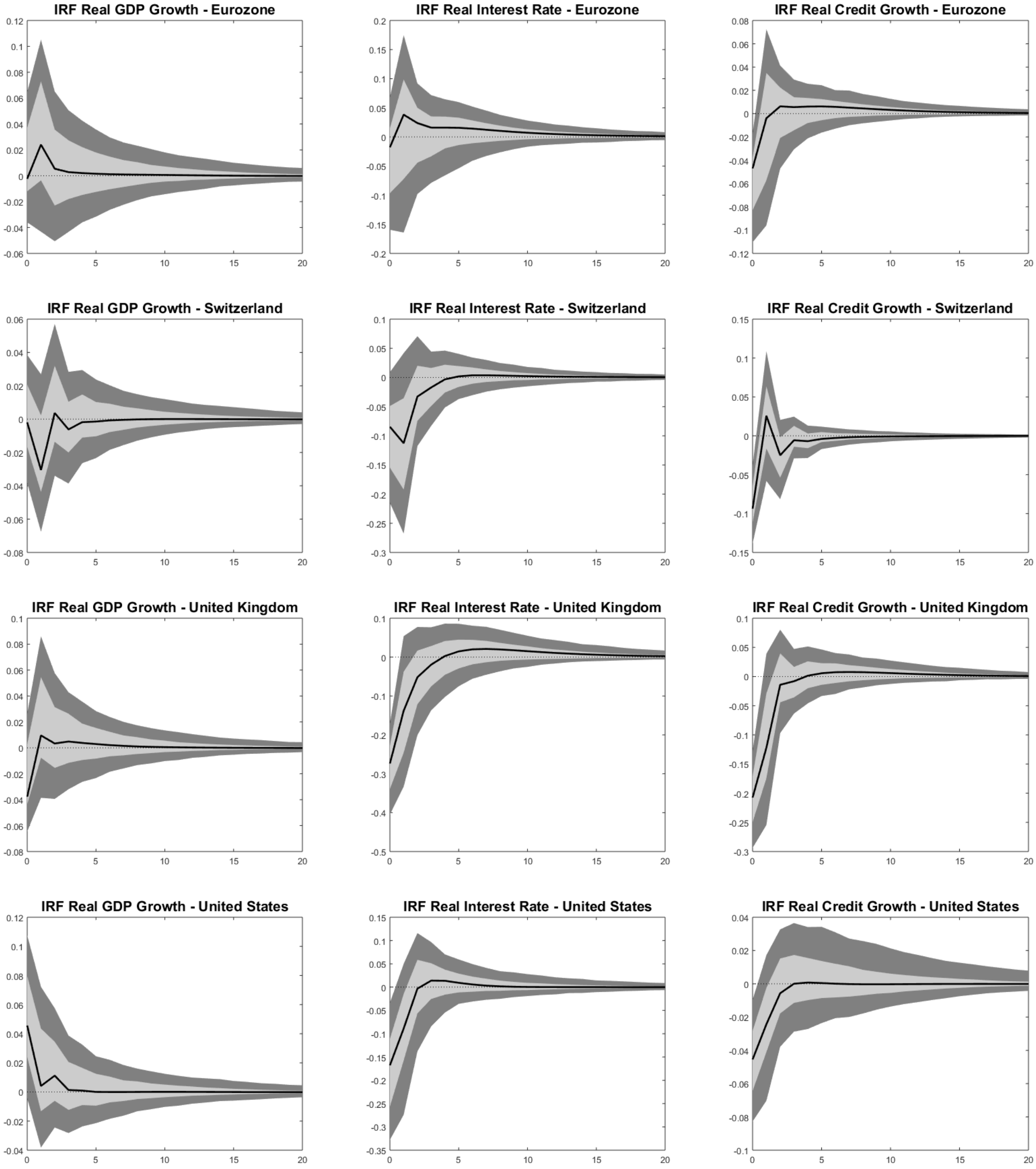
Note: The figure presents the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for aggregate regional real GDP growth of the Model (II) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters.

Figure 4.13: Unit-Specific Impulse Responses - Model (I)



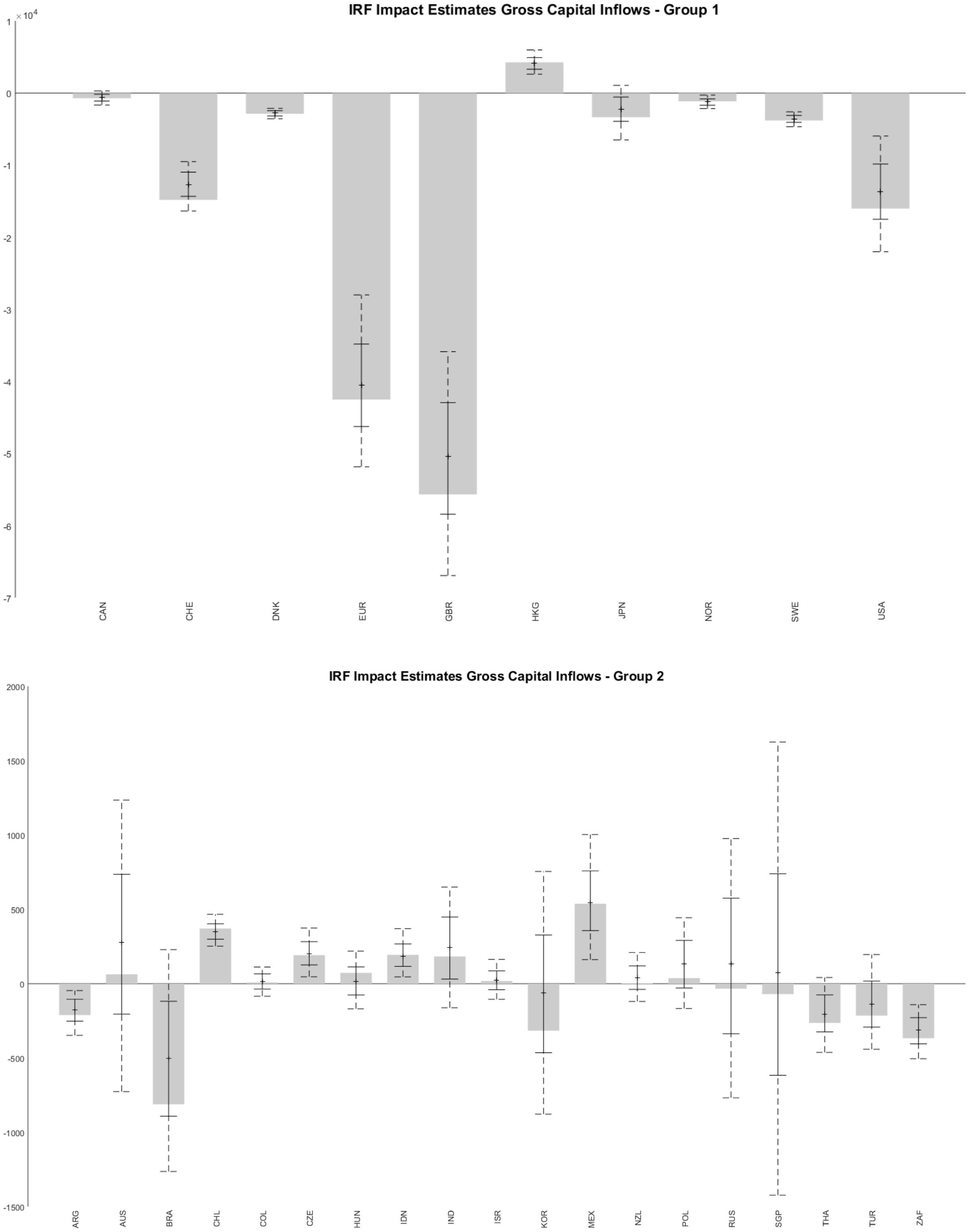
Note: The figure presents the marginal impulse responses of the endogenous VARX variables in the Model (I) GVAR specification together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the eurozone, Switzerland, the United Kingdom, and the United States. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points in case of real GDP growth and the real interest rate and in absolute values in case of capital inflows, respectively, and horizontal axes are in quarters.

Figure 4.14: Unit-Specific Impulse Responses - Model (II)



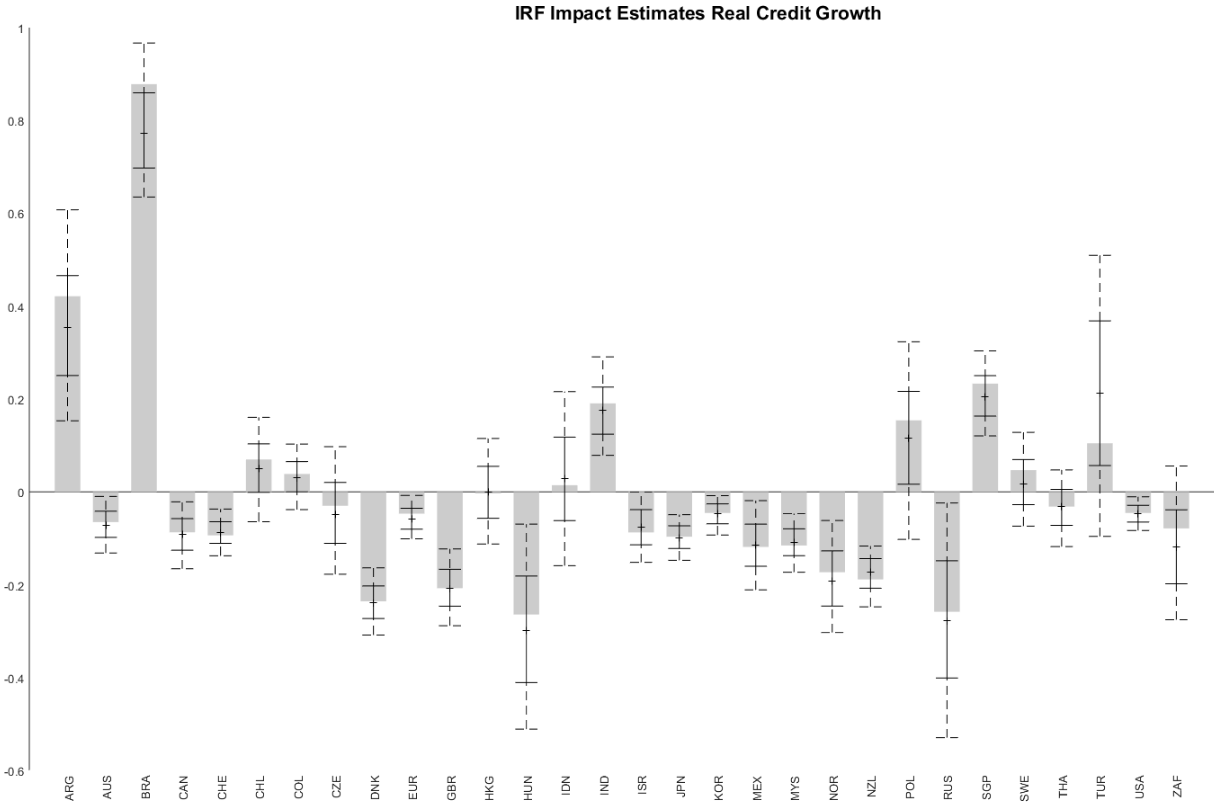
Note: The figure presents the marginal impulse responses of the endogenous VARX variables in the Model (II) GVAR specification together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the eurozone, Switzerland, the United Kingdom, and the United States. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters.

Figure 4.15: Unit-Specific Impact Effect on Gross Capital Inflows - Model (I)



Note: The figure shows the unit-specific impact effect of an European bank balance sheet shock on gross capital inflows in absolute values together with the 68% (solid error bar) and 95% (dashed error bar) confidence interval.

Figure 4.16: Unit-Specific Impact Effect on Real Credit Growth - Model (II)



Note: The figure shows the unit-specific impact effect of an European bank balance sheet shock on real credit growth in percentage points together with the 68% (solid error bar) and 95% (dashed error bar) confidence interval.

Figure 4.17: Grouped Impulse Responses of Real Short-Term Interest Rate and Real GDP Growth - Financial Depth/Development

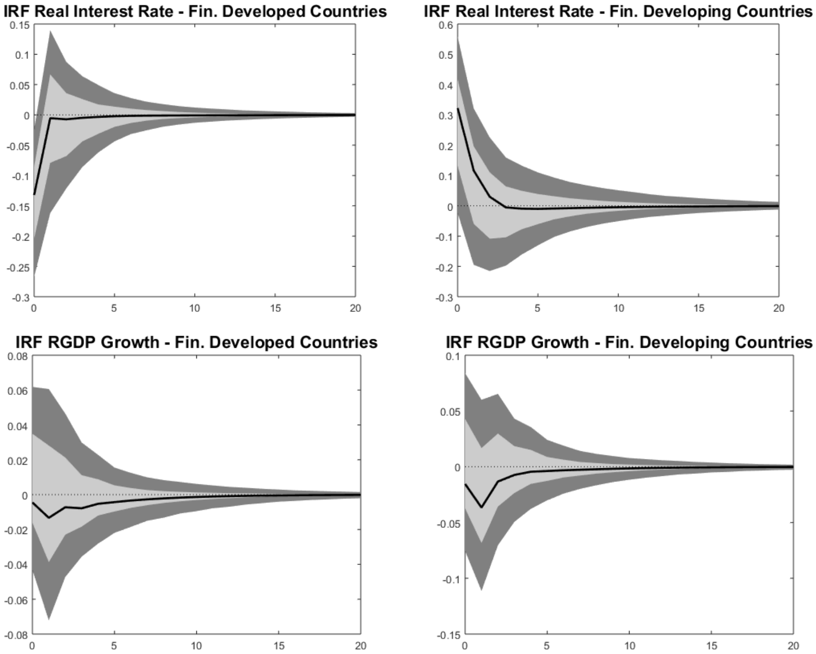
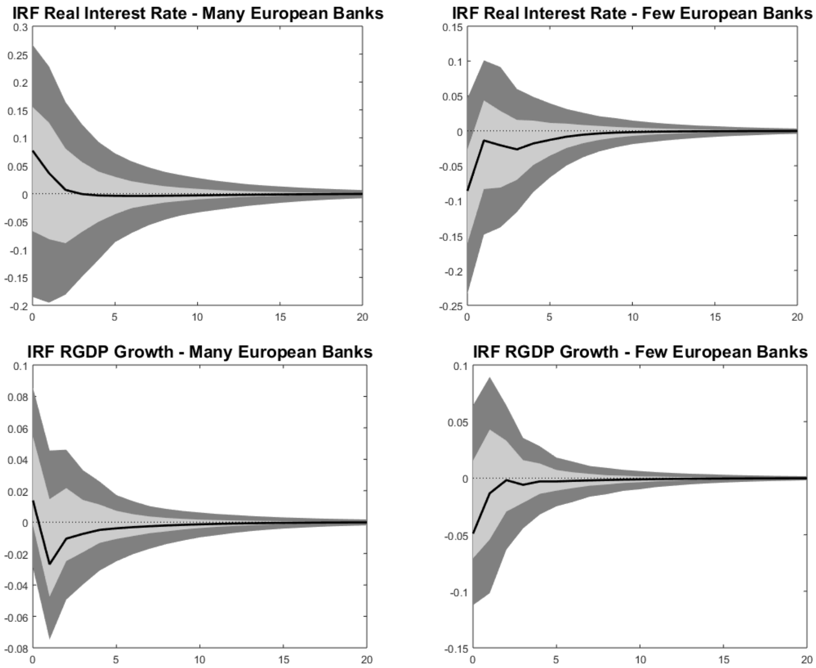
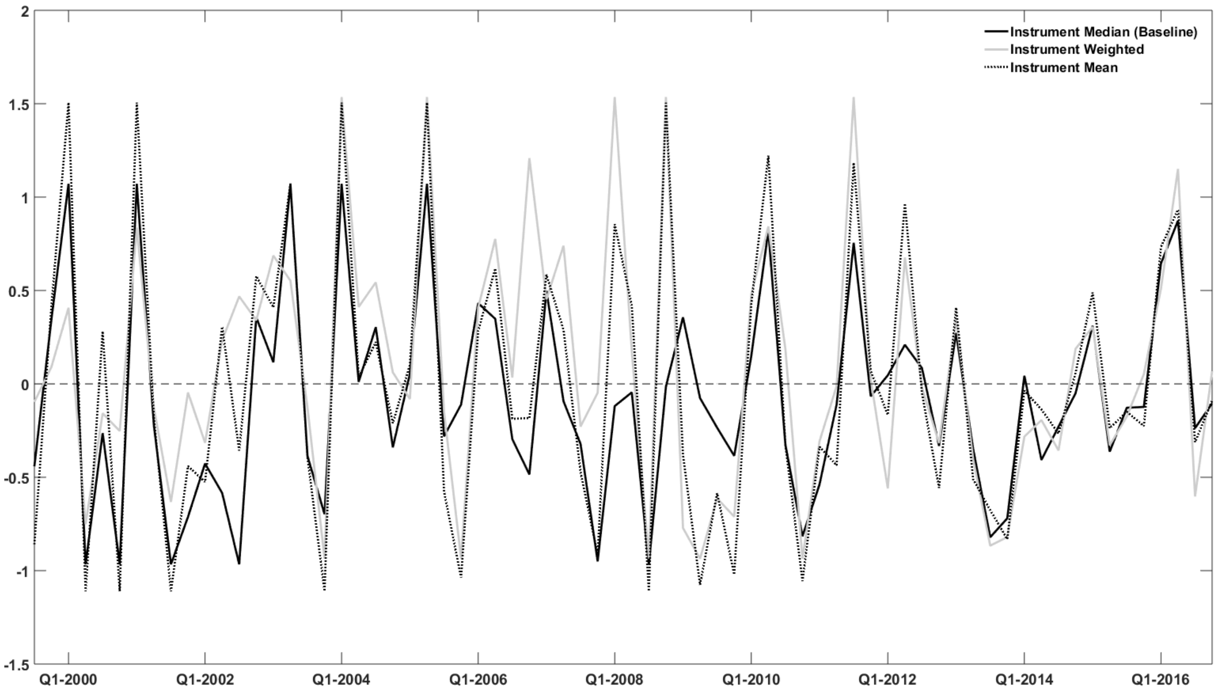


Figure 4.18: Grouped Impulse Responses of Real Short-Term Interest Rate and Real GDP Growth - Number of European Banks



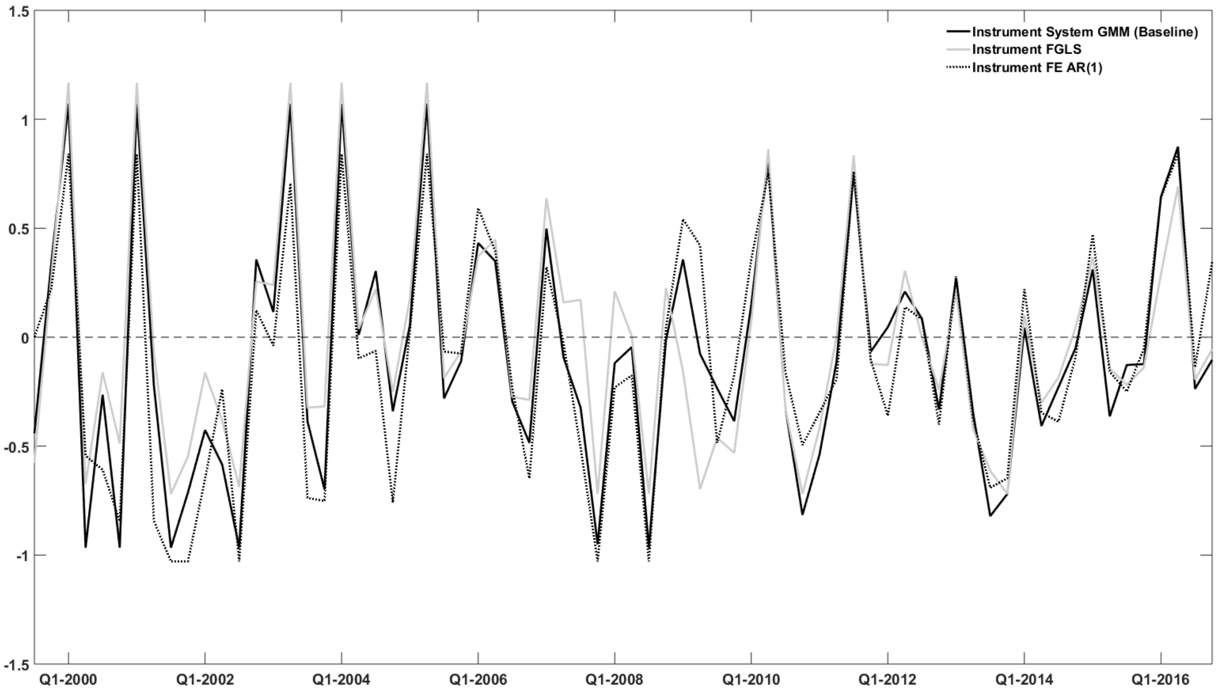
Note: The two figures present the marginal impulse response together with pointwise 68% (light gray area) and 95% (dark gray area) confidence bands for the aggregate grouped real short-term interest rate (upper panel in each figure) and aggregate grouped real GDP growth (lower panel in each figure) of the Model (I) GVAR specification. The confidence bands are based on 1000 bootstrapped replications using a recursive-design residual-based wild bootstrap. Vertical axes are in percentage points and horizontal axes are in quarters. Results of the Model (II) GVAR specification are qualitatively very similar and are available upon request.

Figure 4.19: Comparison with Alternative Instruments (I)



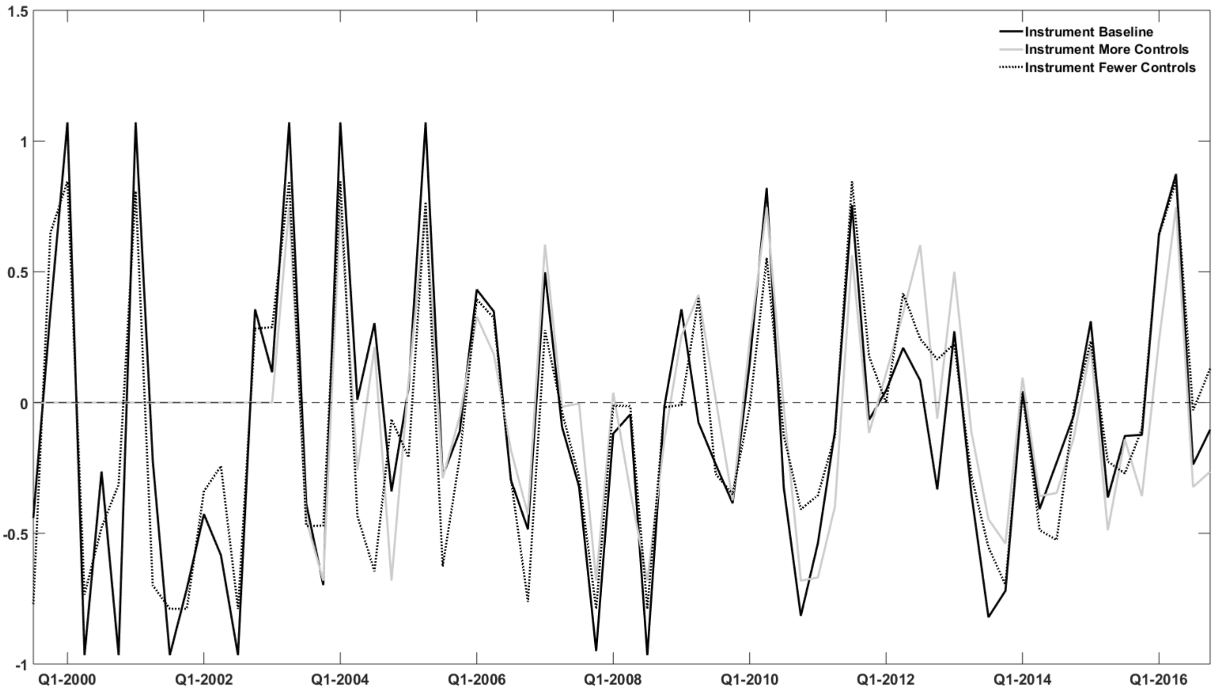
Note: The figure shows a comparison between the baseline instrument (black line), which is derived from taking the median of the bank-individual residuals, and an instrument derived from weighting the bank-individual residuals according to a bank's size measured by total assets (gray line), and an instrument derived from taking the mean of the bank-individual residuals (dotted line).

Figure 4.20: Comparison with Alternative Instruments (II)



Note: The figure shows a comparison between the baseline instrument (black line), which derived from a panel regression applying a two-step system GMM estimator, and an instrument derived from applying a cross-sectional time-series FGLS estimator featuring heteroskedastic errors that follow an individual AR(1) process (gray line) and an instrument derived from applying an OLS fixed effects estimator with AR(1) disturbances (dotted line).

Figure 4.21: Comparison with Alternative Instruments (III)



Note: The figure shows a comparison between the baseline instrument (black line) and an instrument derived from a panel specification that additionally controls for survey-based credit demand in the eurozone (gray line) and an instrument derived from a panel specification that only controls for macro-financial conditions but not for bank-individual characteristics (dotted line).

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Ehrenwörtliche Erklärung

Ich bezeuge durch meine Unterschrift, dass meine Angaben über die bei der Abfassung meiner Dissertation benutzten Hilfsmittel, über die mir zuteil gewordene Hilfe sowie über frühere Begutachtungen meiner Dissertation in jeder Hinsicht der Wahrheit entsprechen.

Ort, Datum

Unterschrift

Liste verwendeter Hilfsmittel

- Matlab Versions 8.4.0.150421 (R2014b), 9.0.0.341360 (R2016a), 9.5.0.944444 (R2018b)
  - Econometrics Toolbox
  - Financial Toolbox
  - Optimization Toolbox
  - Statistics and Machine Learning Toolbox
  - Importance Sampler Algorithm von Arias et al. (2018)
  - GVAR Toolbox von Smith and Galesi (2014)
  - Code zur Identifizierung eines VAR Modells mittels eines externen Instruments von Piffer and Podstawski (im Erscheinen)
- Stata 13.1 & 14.2
- Microsoft Excel 2010, 2011, 2016
- LaTeX
- Siehe auch Literatur- und Quellenangaben